HUMAN DEVELOPMENT
REPORT 2025

UNDP

A matter of choice: People and possibilities in the age of AI

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The 2025 Human Development Report

The cover and chapter images in the report feature portraits in the artistic styles of various historical periods and cultures, with subtle allusions to people's use of technology.

For example, the cover presents a modern woman with headphones, against a background with hints of technology in the style of prehistoric cave paintings—an echo of humanity's earliest attempts to understand and shape the world.

Combining history with symbols of modern technology, the images place humans at the centre and aim to bridge the past and future—positioning today's breakthroughs in artificial intelligence (AI), and the media through which we interact with them, as part of humanity's unfolding and open-ended journey towards advancing human development.

Working with AI, a graphic designer created the images by guiding the system with ideas and creative direction, prompting the AI to produce a range of visual outputs that the graphic designer then edited, developed and finalized. The artworks themselves reflect how AI could reshape how we do things, unleashing new creative possibilities and augmenting what people can do. The cover and other images invite you to pause and reflect—as we navigate the uncertainties and possibilities of a world with AI.

HUMAN DEVELOPMENT
REPORT 2025

A matter of choice

People and possibilities in the age of AI

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Foreword

Artificial intelligence (AI) is racing ahead at lightning speed. Yet as AI surges forward, human development stalls. Decades of progress, reflected in the Human Development Index, have flatlined, with no clear recovery from the blows dealt by the Covid-19 pandemic and subsequent crises. We are at a crossroads: while AI promises to redefine our future, it also risks deepening the divides of a world already off balance. Are we on the verge of an AI-powered renaissance—or sleepwalking into a future ruled by inequality and eroded freedoms?

Too often, headlines, policies and public debates fixate on what AI might achieve in some distant future—utopian or dystopian. These deterministic views are not only disempowering; they are profoundly misleading. They obscure the fact that the future is being shaped now, by the choices we make today. The 2025 Human Development Report, A Matter of Choice: People and Possibilities in the Age of AI, reminds us that it is people—not machines—who determine which technologies thrive, how they are used and whom they serve. AI's impact will be defined not by what it can do but by the decisions we make in its design, development and deployment.

Central to these decisions is how we view the role of people in an AI-driven world. Assuming that AI will inevitably sideline humanity overlooks the very force driving its progress: us. AI's capacity to automate nonroutine tasks has stoked fears of human replacement—but this is only when we reduce people to mere task-performers. This Report challenges that view. It argues that humans, "the true wealth of nations," are far more than the sum of the tasks we perform. Rather than measuring AI by how closely it mimics us, the Report emphasizes how the differences between humans and machines can create powerful complementarities that expand human potential.

This people-centred perspective becomes even more critical in a moment of overlapping global crises. It is tempting to believe that AI alone can solve our development challenges. But that belief invites complacency. It asks us to surrender responsibility and ignore the political, social and systemic barriers that have long impeded progress. The 2023/2024 Human Development Report, *Breaking the Gridlock*, made it clear: our limitations are not technological but sociological. Many of the crises and inequalities we face persist not because solutions are lacking but because we have failed to act. With AI we must choose differently—and we must choose now.

We might resist the temptation to anthropomorphize AI, yet in many ways it acts like a mirror—reflecting and amplifying the values, structures and inequalities of the societies that shape it. AI does not act independently of us; it evolves through our decisions and our priorities. If we fail to address the injustices and divides that persist today, AI will only entrench them further. But if we invest in human capabilities and commit to greater equity, AI can magnify the best of what humanity can achieve. Ultimately, the 2025 Human Development Report on AI is not about technology—it is about people, and our ability to reinvent ourselves in the face of profound change.

Achim Steiner
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Every Human Development Report is a voyage of discovery, exploring how the human development approach helps navigate pressing challenges and emerging opportunities. That navigation proved particularly challenging for this Report, given the rapidly changing context of artificial intelligence (AI). AI continues to astonish every day. It engenders a mix of hype and hope, along with fear and trepidation. It is attracting financial investment and human talent towards its continuing evolution, but it is also becoming a source of geopolitical tensions. There was really no roadmap helping us navigate what seemed like a new and constantly moving AI frontier. A technology that is in many ways just one more like many others that preceded it also felt at times different, in its ability to simulate and replicate features that are so distinctively human. Therefore, this is a Report that captures the spirit of a particular moment in time, with much uncertainty about what might follow in terms of both AI as a technology and its ultimate impact on people's lives. Joining in this journey of exploration are the many individuals and organizations recognized here that contributed their expertise, wisdom and expectations, as well as doubts, about what AI might mean for human development.

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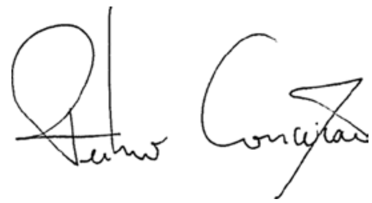

Pedro Conceição
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A matter of choice

People and possibilities in the age of AI

A matter of choice: People and possibilities in the age of AI

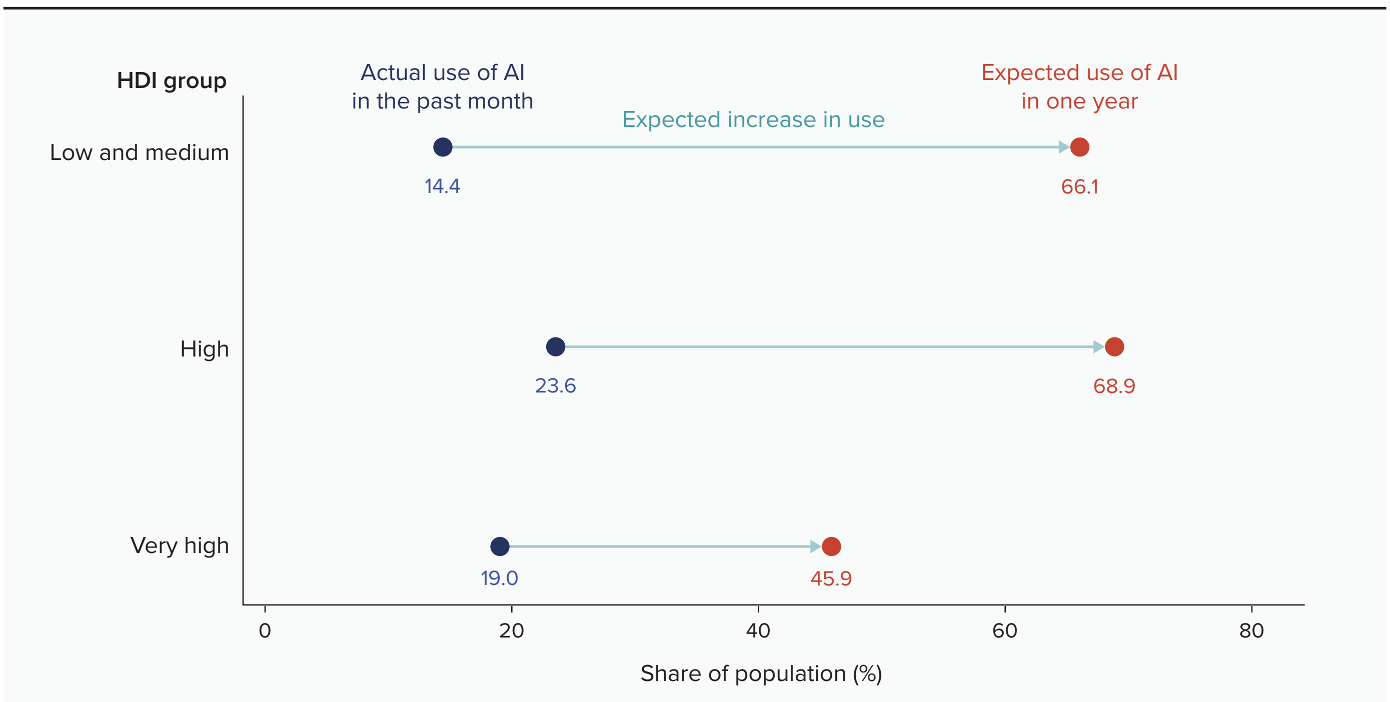
Artificial intelligence (AI) has broken into a dizzying gallop. Each day seems to herald some new AI-powered algorithmic wonder. As a general-purpose technology, AI has been dubbed "the new electricity." Regardless of whether the utopian, techno-solutionist[1] visions of AI's most ardent advocates come to fruition or fizzle as snake oil (or worse), the world is pulsing with a powerful new technology, a new kind of dynamism or vitality, that differs from technologies of the past.

Yet, the AI zeitgeist is awfully blinkered. Headlines fixate on arms races, policymaking on risks. These are real. But they are not—and should not be—the whole story. We need to go beyond races and risks to possibilities for people, possibilities shaped by people's choices.

The choices that people have and can realize, within ever expanding freedoms, are essential to human development, whose goal is for people to live lives they value and have reason to value. A world with AI is flush with choices the exercise of which is both a matter of human development and a means to advance it. The future is always up for grabs, even more so now. Trying to predict what will happen is self-defeating, privileging technology in a make-believe vacuum over the frictional realities and messier promises of people's agency and their choices. From a human development perspective the relevant question instead is what choices can be made so AI works for people.

This year's Human Development Report examines what distinguishes this new era of AI from previous digital transformations and what those differences could mean for human development (chapter 1), including how AI can enhance or subvert human agency (chapter 2).[2] People are already interacting with AI in different ways at different stages of life, in effect scoping out possibilities good and bad and underscoring how context and choices can make all the difference (chapter 3). Human agency is the price when people buy into AI hype, which can exacerbate

Figure O.1 About two-thirds of survey respondents in low, medium and high Human Development Index (HDI) countries expect to use artificial intelligence in education, health and work within one year



Note: Based on pooled data for 21 countries. For actual use in the past month, the following responses to the question, "In the past 30 days, have you ever interacted with artificial intelligence, such as chatbots, in any of the following ways?" were used to calculate the average use of AI for education, health and work: "education" is based on the response "educational platforms of learning apps," "health" is based on the response "health care services or applications" and "work" is based on the response "work-related tools or software." For expected use in one year, the following responses to the question, "Over the next 12 months, how likely are you to use an artificial intelligence tool for the following?" were used to calculate the average use of AI for education, health and work: "education" is based on the response "for education and training," "health" is based on the response "for medical advice" and "work" is based on the response "for work tasks." Expected increase in use is the difference between expected use in one year and actual use in the past month.
Source: Human Development Report Office based on data from the United Nations Development Programme Survey on AI and Human Development.

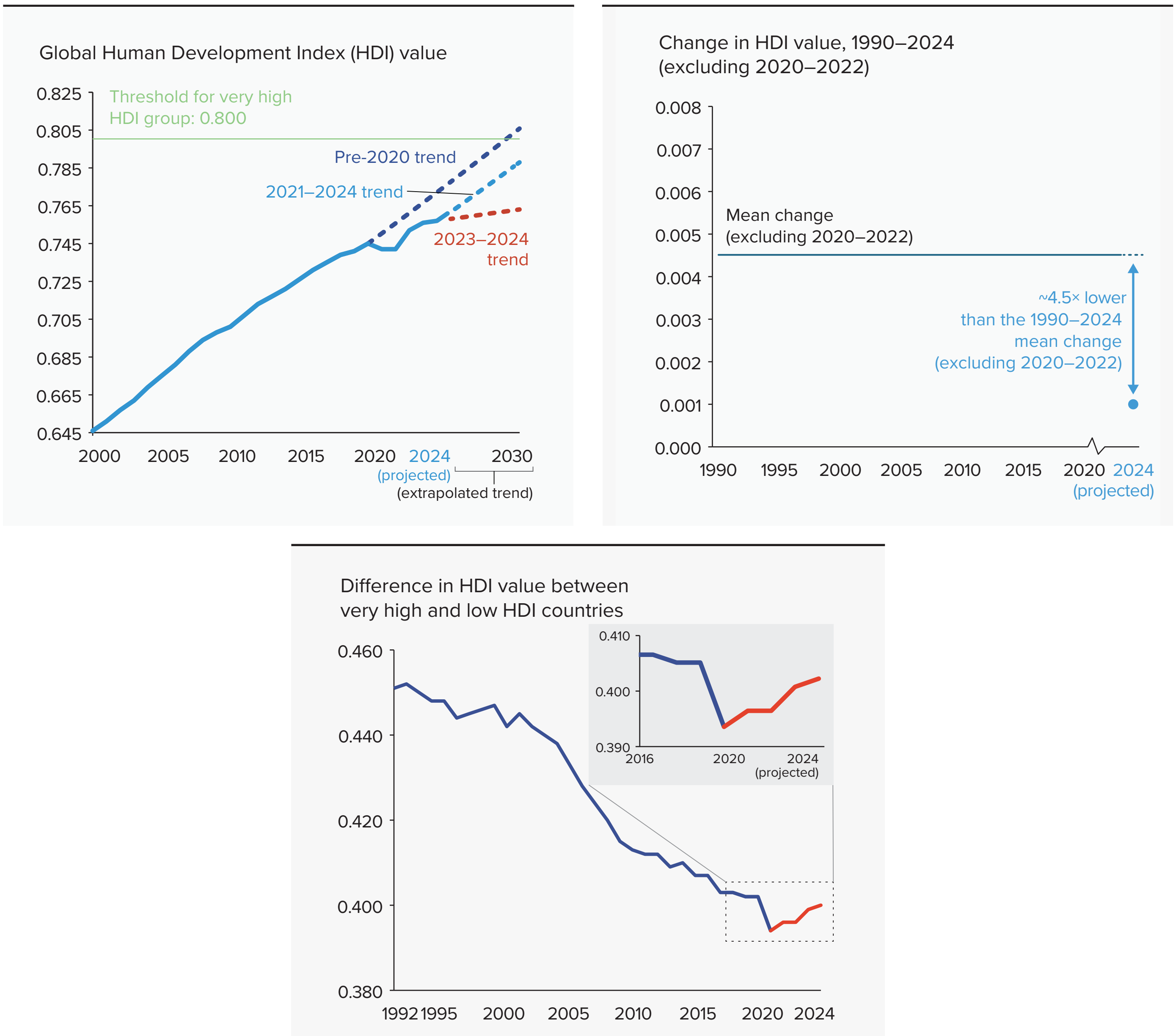
exclusion (chapter 4) and harm sustainability.[3] And, of course, who produces AI and for what matter a lot for everyone (chapter 5).

Letting people take the reins makes good sense, because they expect AI to be a growing part of their lives. A global survey[4] for this Report found that, at all levels of the Human Development Index (HDI), AI use is already substantial (for about 20 percent of respondents) and is expected to shoot up fast. About two-thirds of respondents in low, medium and high HDI countries expect to use AI in education, health and work—the three HDI dimensions—within one year (figure O.1).

Human development gaps are widening, and global progress may be losing steam

Focusing on people can help many countries feeling caught in a human development pinch between

Figure O.2 Global progress in human development is losing steam, with the weakest and most vulnerable being left farther behind



Source: Human Development Report Office calculations based on data from Barro and Lee (2018), IMF (2024), UNDESA (2024), UNESCO Institute for Statistics (2024), United Nations Statistics Division (2025) and World Bank (2024).

sky-high expectations for AI and sobering development realities, including ongoing violent conflicts and stresses on human security. Wounds from the 2020–2021 declines in global HDI value have not healed, and the rebound since may be losing steam. Just a few years ago we were on course to live in a very high HDI world by 2030.[5] That world was delayed by a few years based on the 2021–2024 trend. Now it is projected to be delayed by decades (top left panel of figure O.2).[6]

While the global HDI value is projected to reach a record high in 2024, the increase would be the lowest since records began 35 years ago (top right panel of figure O.2). Gaps between very high and low HDI countries, which for decades had been shrinking, have been widening over the past four years (bottom panel of figure O.2). The dramatic slowdown in HDI progress cuts across all developing regions (figure O.3).

Development pathways that have created jobs at scale and reduced poverty, thanks to expanded manufacturing and exports to international markets, are narrowing.[7] A triple squeeze results from inadequate external financing, fewer opportunities in manufacturing due in part to automation and trade tensions limiting export options.[8]

Now enter AI, a development wildcard.[9] If AI is seen simply as a supercharged extension of earlier digital technologies deployed to automate work, labour is condemned to cede the remaining ground to machines, further eroding development options. Is this what is in the cards?

It is a matter of choices. Development depends less on what AI can do—not on how human it appears—and more on mobilizing people's imaginations to reshape economies and societies to make the most of it.

Figure O.3 The post-2020 slowdown in human development progress affects every region of the world

Source: Human Development Report Office calculations based on data from Barro and Lee (2018), IMF (2024), UNDESA (2024), UNESCO Institute for Statistics (2024), United Nations Statistics Division (2025) and World Bank (2024).

Making AI work for people is a matter of choices

AI does some things uniquely well, such as seeing patterns in huge datasets that are difficult or impossible for humans to discern.[10] It does other things poorly, sometimes making things up.[11] It cannot frame problems, as humans can do. Whatever new algorithmic feats are in store, there will always be spaces, however in flux, where humans shine—where humans do things that machines cannot do or are bad at, where societies value people rather than machines doing things and where people and machines go farther and faster together than separately.

Evolving overlaps and complementarities between humans and AI-powered machines land societies at inflection points, after which trajectories will depend largely on two factors: what access societies have to AI and how they view and use it. These are choices, by the few or the many. Is the focus on overlaps, pitting what Daron Acemoğlu calls so-so AI against people, which could cut jobs without productivity gains?[12] Or is it instead on complementarities and collaboration to envision new development pathways?[13] Entirely new roles, markets and industries could be in the offing. If anything, then, AI can be seen as adding hazy pages to the development playbook instead of stripping them away. Possible paths become wider, if less clear, given that much is yet unknown about what AI can do and how it will affect human decisions.

> “AI can be seen as adding hazy pages to the development playbook instead of stripping them away. Possible paths become wider, if less clear, given that much is yet unknown about what AI can do and how it will affect human decisions

People seem to expect as much: a cloudy glass half full. Nearly 4 in 10 respondents[14] in the survey for this Report expect AI to automate and augment jobs. Overall expectations for augmentation (61 percent) just edge those for automation (51 percent).[15] And the more that people use AI, the more confident they feel in its ability to increase productivity. Expectations in developing countries are particularly high.[16] With so much promise and expectation, the bar for AI is higher than simply being useful or “doing good”; it is avoiding development disappointment.

It is time to break the spell of technological inevitability: no path forward is about technology in isolation but rather how it is deployed—by whom, with whom, for whom—and with what kind of accountability. Different choices can help turn things around, and the lens of this year’s Human Development Report, focused on people and possibilities, identifies three areas of action for AI-augmented human development (chapter 6):

1. *Building a complementarity economy,* so people and AI find more opportunities to collaborate rather than compete.

   Rather than try to predict the future, policymakers should shape it, breaking away from trying to guess how humans will be replaced by AI, to see the potential of what humans can do with AI. That includes driving productivity gains through intelligence augmentation, leveraging the complementarities between AI and people. Ensuring that AI is proworker, limiting curbs on agency and empowering workers to use AI to augment what they can do. Deploying AI in sectors where positive spillovers to other sectors and across the economy can be leveraged, helping with economic diversification and job-creating structural transformation. Implementing fiscal measures and strengthening social dialogue that incentivize AI to safeguard decent work and supporting incumbent workers displaced by AI.

2. *Driving innovation with intent,* so opportunity for people is not an afterthought but a built-in integral part of AI design and deployment.

   AI should be harnessed to accelerate science through curiosity-driven basic research, as well as technological innovation—not by automating creative processes but by augmenting them.[17] AI innovation can be steered through incentives that embed human agency in AI from design to deployment—by aligning socially desirable and privately profitable innovation and supplementing existing AI benchmarks with new ones that capture AI’s potential to advance human development.

3. *Investing in capabilities that count,* so people have the capabilities to make the most of AI in their lives and to thrive in a world with AI.

   AI’s flexibility and adaptability should be leveraged to personalize education and healthcare in different contexts, while attending to risks and concerns related to bias, privacy, affordability and equity.[18] By tailoring learning or expanding health care, AI can also generate demand for complementary human labour.[19]

Together, the three areas invite policymakers at different levels to shake off unhelpful narratives that swing between utopia and dystopia, to depart from disempowering trends that sideline most people or put bullseyes on their backs and instead to embolden people to reimagine their choices and expand their freedoms.

Who, where, when and how? AI's possibilities depend on context

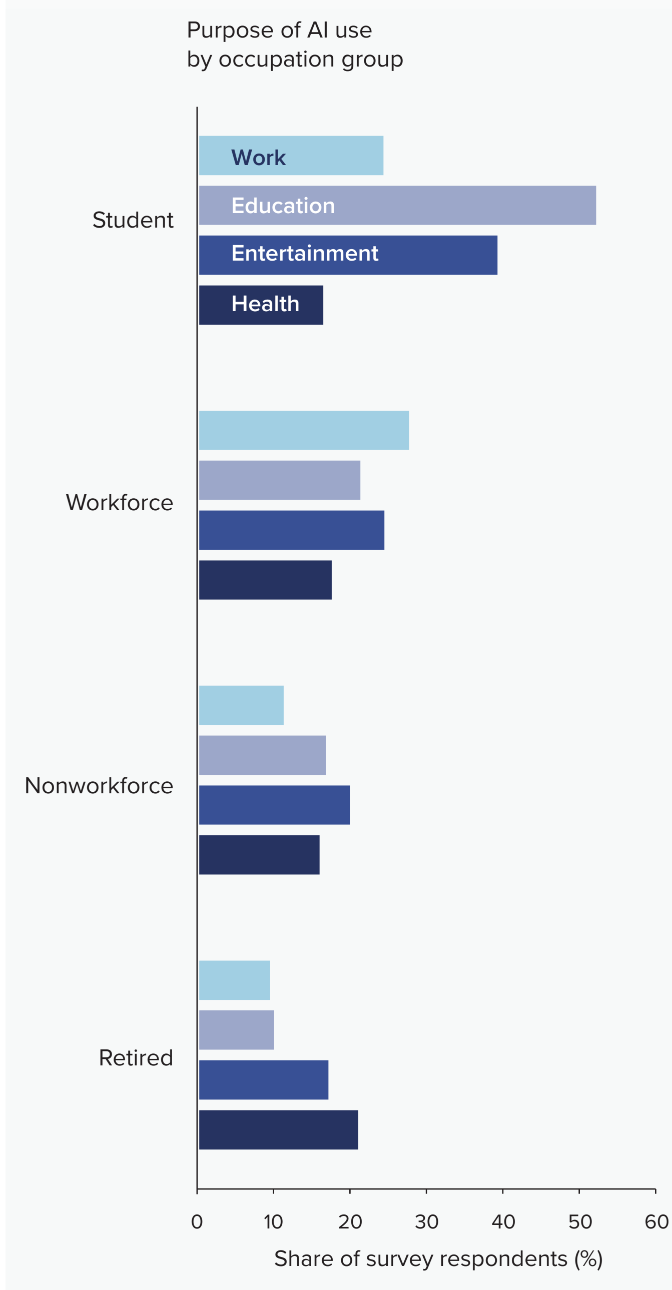
The possibilities of AI depend on context: who, where, when, how? AI is more than just an opportunity for people's choices; it requires them. People of different ages use AI for different purposes (figure O.4). AI has shown promise for helping students by providing study assistance when educators or parents have time or resource constraints[20] or by improving personalized, adaptive learning.[21] AI could bridge gaps in the light of constrained education resources and help level the field for disadvantaged students.[22] This is in addition to—not in lieu of—teachers, who uniquely provide, among other things, necessary social interactions critical to students' overall development.

Until recently, one of the most well-established empirical regularities across countries was that subjective measures of wellbeing (such as life satisfaction) followed a U-shaped pattern with age: younger and older people reported higher wellbeing than those in middle age (late 40s to early 50s).[23] About 10–15 years ago that began to change in some countries. Despair among young people shot up, and life satisfaction tanked.[24] Young women fare worse than young men.[25]

What explains the dramatic declines among young people? The picture is complex and evolving. That the trend is most evident in some very high HDI countries and parallels the broader diffusion of smartphones has implicated digital technologies. In a global survey of people with access to the internet, the typical U-shape curve is completely absent. In its place is essentially a diagonal line, with young people's mental wellbeing at the bottom (figure O.5).[26]

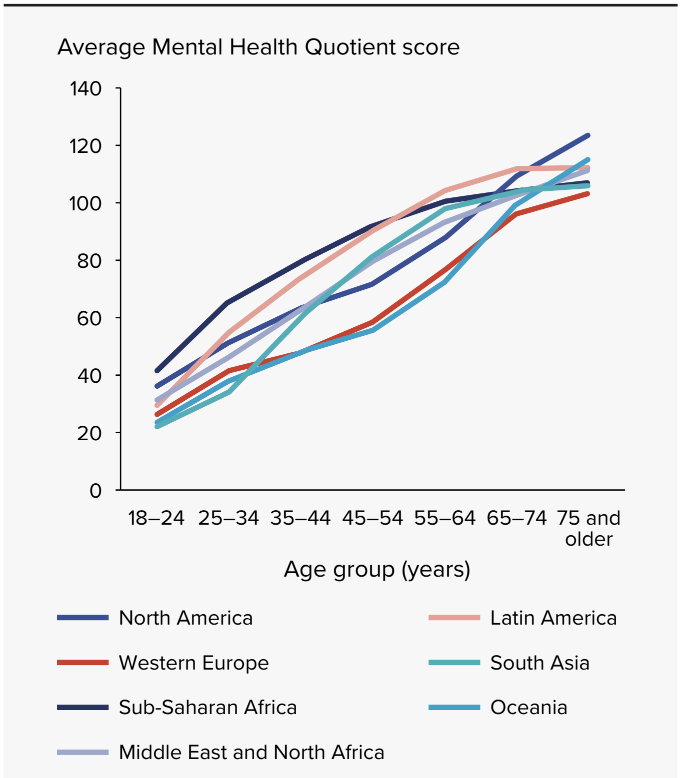
The opportunities for and risks to young people from digital technologies, including AI, are

Figure O.4 People at each life stage use artificial intelligence (AI) for different purposes



Note: Based on pooled data for 21 countries. For purpose of AI use, the following responses to the question, "In the past 30 days, have you ever interacted with artificial intelligence, such as chatbots, in any of the following ways?" were used to calculate the average use of AI for work, education, entertainment and health: "work" is based on the response "work-related tools or software," "education" is based on the response "educational platforms of learning apps," "entertainment" is based on the response "entertainment (e.g. streaming services/gaming)" and "health" is based on the response "health care services or applications." For occupation group the following responses to the question "What best describes you? Are you...?" were used: "working" includes self-identified full- and part-time employees and self-employed respondents, and "not working" includes homemakers and unemployed respondents.
Source: Human Development Report Office based on data from the United Nations Development Programme Survey on AI and Human Development.

Figure O.5 Young internet users are struggling—everywhere



Note: Data are from the Global Mind Project at Sapien Labs. The Mental Health Quotient score is a tool that encompasses 47 aspects of mental function assessed on a life impact scale that span the dimensions of Mood & Outlook, the Social Self (or relational aspects), Adaptability & Resilience, Drive & Motivation, Cognition and Mind-Body Connection. The higher the score, the better perceived mental wellbeing. The survey was conducted during 2020–2024.
Source: Thiagarajan, Newson and Swaminathan 2025.

particularly relevant for many lower HDI countries, where age structures skew young and digital penetration has farther to go. That is itself an opportunity to chart a path informed by lessons elsewhere. The age structures of many higher HDI countries lean the other way, towards the old. Although patterns differ across countries, the world as a whole is greying quickly, with 1.4 billion people age 60 or older expected by 2030.[27] At the same time younger people expect to lose control over their lives due to AI less than older people do (figure O.6).

AI has enabled pathbreaking innovations in assistive and accessible technologies that can expand choices and opportunities for people with disabilities, technologies such as live captioning, image descriptions and translation of sign language into voice or text.[28] But achieving the full reach and potential of these and other applications depends on more than technology alone. Social choices and contexts matter, too,[29] including, at the most fundamental level, whether these applications are accessible and affordable. Likewise, gender inequalities permeate both the production and consumption of AI. The survey for this Report finds that irrespective of education qualifications, men are more likely than women to use generative AI for work.[30]

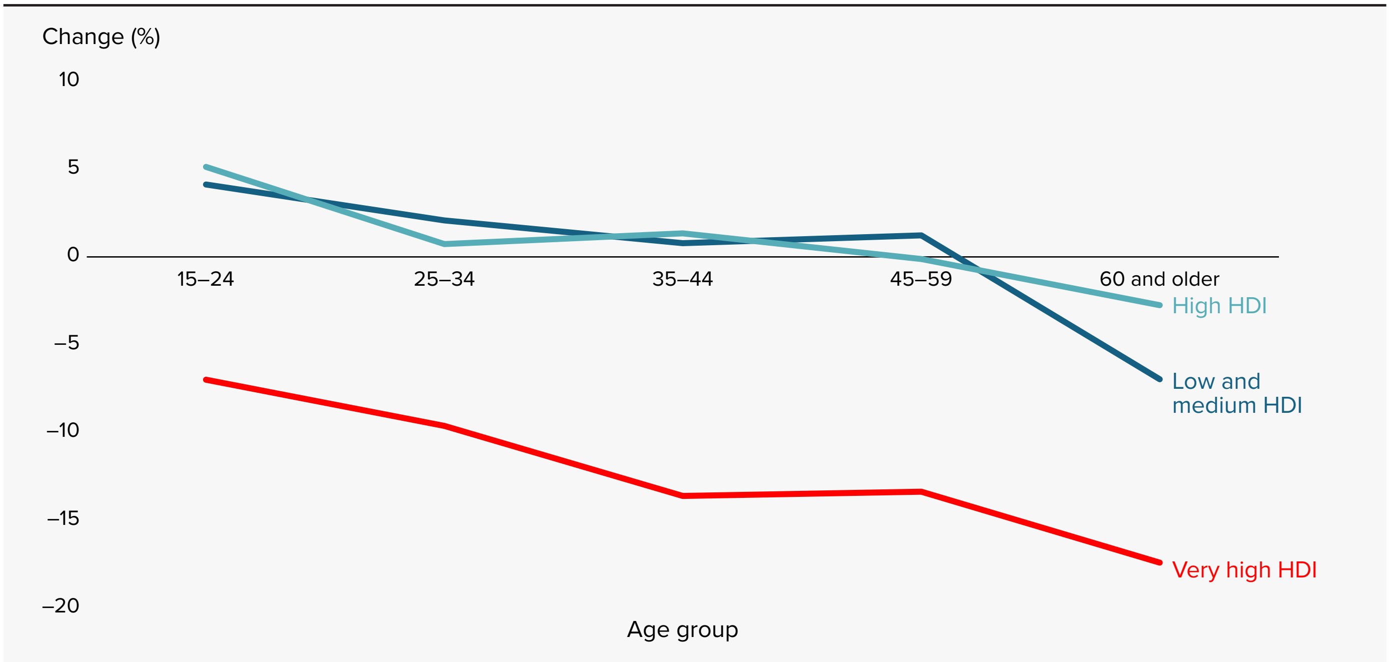
Building a complementarity economy

Seemingly every day, a new AI model exceeds human scores on a narrowly defined benchmark, often bearing apocalyptic sobriquets such as Humanity's Last Exam. From this supply-side view humans are framed as one-dimensional benchmarks in a zero-sum competition for finite spots in our future economy—an economy of human replacement. Yet incorporating the demand side reveals how policy choices and strategies can promote a complementarity economy, where AI could augment and extend existing human labour,[31] yield a more inclusive labour market[32] and lead to new industries, jobs and tasks.[33]

AI can automate tasks that have long remained resistant—nonroutine tasks that cannot be accomplished by some industrial machine. Yet rarely do jobs comprise solely what can be readily delegated to machines. Consider radiologists, who were viewed a decade ago as at risk of no longer being needed following the success of AI in interpreting radiological imagery. Today, demand for radiologists remains as high as ever.[34] AI diagnosis is a far cry from deploying medical knowledge in a clinical setting—which, even if it were feasible, patients might reject.[35] A decade on, the story of AI in radiology is one of complementarity—improving diagnostics through AI that augments rather than replaces radiologists.[36]

AI's capacity for augmenting human abilities can likewise serve as a vital onramp for economic inclusion. For example, AI tends to improve the performance of newly hired call centre workers but has lesser effects for seasoned veterans.[37] Similar results have been documented in writing tasks,[38] software development[39] and management consultancy,[40] among others.[41] Firms are adopting AI for product innovation more than for process automation and seeing higher sales, revenue and employment through better outputs.[42]

Figure O.6 Younger people expect to lose control over their lives due to artificial intelligence (AI) less than older people do



Note: Based on pooled data for 21 countries. Data show, for each age group, the change in perceived agency as measured by the difference in the percentage of respondents who feel they have a high level of control over their lives today and the percentage who expect to feel a high level of control five years from now, as AI becomes more integrated into everyday life.
Source: Human Development Report Office based on data from the UNDP Survey on AI and Human Development.

As AI systems are integrated into jobs, working effectively alongside AI—understanding its limitations, interpreting its outputs and applying human judgement—will be critical. New kinds of tasks and related expertise will be needed at the nexus of people and machines. Some envision three new roles: explainer, trainer and sustainer.[43]

Yet AI can disrupt and displace work. Robust social protection systems alongside adaptive skills building aligned with emerging needs can improve employment prospects,[44] while on-the-job training may support those whose jobs and tasks are reshaped by AI.[45] AI systems rely heavily on human labour throughout the supply chain, from development and design to data labelling and annotation.[46] As an AI-enabled economy expands, social dialogue and collective bargaining are key for new meaningful decent work opportunities.

Labour augmentation opportunities, despite their big potential, are not inevitable. The digital divide persists, such that access and relevant skills are limiting factors for using technology more broadly, and these challenges apply equally to AI in the workplace. Starting nearly a generation ago, digital technologies began suffusing high-income countries, whose workforces today typically enjoy widespread access to digital devices and have extensive experience using them.[47] Elsewhere the persistent digital divide is likely to be a major barrier to realizing the positive effects of AI on jobs and beyond.[48]

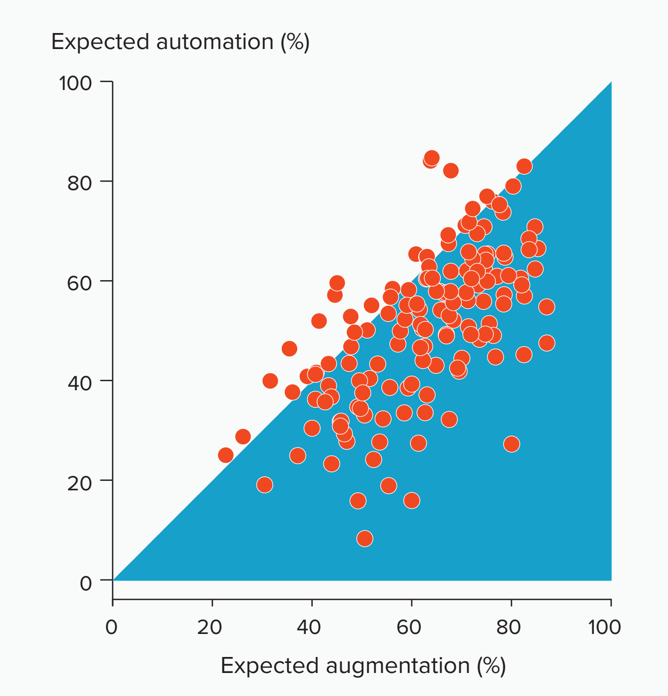
Looking ahead, people expect AI to both automate and augment their work, but they expect the balance to tilt towards augmentation (figure O.7).

Whether the expectations for augmentation will be met depends on policies and incentives to catalyse complementary between people and AI. Getting this wrong will lead to development disappointment in the short term and possibly wider economic divergence in the coming decades. One possibility is averting hasty worker replacement caused by deployment of so-so AI that destroys jobs without generating productivity gains and instead promoting fiscal policies that encourage augmentation.[49]

Driving innovation with intent

AI can accelerate discovery and innovation and trigger new frontiers of creativity,[50] potentially becoming a method of invention.[51] That is, a new tool to

Figure O.7 Across occupations and Human Development Index levels, respondents expect that artificial intelligence will both automate and augment their work—with higher expectations of augmentation



Note: Based on pooled data for 21 countries. Each dot represents the percentages of respondents in an occupation group in a country who expect automation and augmentation from AI to affect their occupation. The following occupational groups are used: professional/higher administrative, skilled, unskilled/semi-skilled, services, clerical, farm and other. The shaded area represents a higher share of respondents expecting augmentation than automation.
Source: Human Development Report Office based on data from the United Nations Development Programme Survey on AI and Human Development.

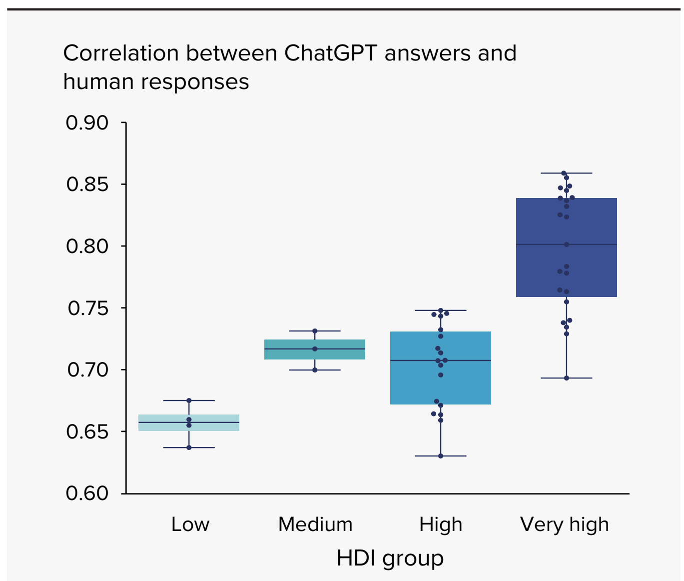
empower people to fulfil the deeply human aspirations to understand and create. Rather than automating tasks in creative processes associated with scientific and technological innovation, the key is augmenting human intelligence[52] by leveraging the complementary capabilities of AI and humans to accelerate innovation[53] and creativity more broadly.[54]

The direction of AI innovation could be steered in ways that align with socially desirable and privately profitable outcomes.[55] AI benchmarks have become fundamental tools for evaluating the performance, capabilities and safety of AI models.[56] Supplementing the current lot with new standards that assess AI's contribution to human development could help steer AI innovation in that direction.[57]

The complex intersection of different country priorities with global and local constellations of tech firms is fuelling a geopolitical innovation race that risks leaving many countries and people behind.[58] The mismatch between suppliers and users matters for many reasons. One is cultural. AI models reflect the cultures where they were developed. ChatGPT responses are closer culturally to those of humans in very high HDI countries and most distant from those in low HDI countries (figure O.8).

Combatting cultural and linguistic bias is one reason many countries desire to be part of the AI supply chain. AI supply depends on three key inputs—computing power, data and talent—some of which are highly concentrated, posing unique challenges to many lower HDI countries. Only a handful of voices wield power over and through AI. Few of us have much direct say over it. What choices trickle down to us may seem atomizing and binary: buy the latest gadget or not, accept the cookies or not. Take-it-or-leave-it terms of service agreements can boil down to granting powerful firms carte blanche access to our daily lives or to being excluded from digital platforms, where for better or worse ever more of our lives, interactions and relationships take place.

Figure O.8 ChatGPT answers are culturally closer to those of humans in very high Human Development Index (HDI) countries



Note: Higher values on the vertical axis indicate greater cultural and values similarity between ChatGPT and respondents in a given country (indicated by a dot).
Source: Based on data from Atari and others (2025), who compared results across 65 countries from the World Values Survey.

Narratives that focus on and reinforce only zero-sum thinking crowd out opportunities where cooperation could add a lot of value. At the global level opportunities for international cooperation on AI exist, not necessarily on everything but certainly in some specific and important areas. The rationale is especially compelling in computer-provided oversight, content provenance and model evaluations.[59] Indeed, important work across many international institutions and fora are well under way. The UN Global Digital Compact, which encourages cross-jurisdiction and science-informed dialogue can enable countries to learn from each other and fine-tune regulatory approaches, as well as level the playing field so all countries can meaningfully participate in and benefit from AI's potential.

Investing in capabilities that count

To prepare young people to strive with AI, education needs to focus on learning outcomes, as well as critical, creative and relational thinking, moving beyond simply increasing years of schooling. When integrating AI in education, avoid using AI as a crutch, by teachers or students, and treat it as a companion to unleash new ways of learning. This involves deploying AI to scale interventions known to enhance education outcomes, such as customized learning, rather than deploying it for its own sake.

In healthcare AI should be deployed to complement expertise, particularly when it is scarce, as in lower-income countries and settings, empowering healthcare workers to do more in resource- and expertise-constrained contexts.[60] Healthcare systems and organizations should safely and transparently integrate AI technologies—strengthening both institutional and frontline provider capacity to use these systems, while clearly communicating to patients how the systems are employed in clinical decisionmaking to build trust. Because the unintended side effects of AI in health services may change over time, monitoring AI biases and health inequalities needs to be seen as continuous.[61]

New horizons for human development

Scientific and technological progress propel development.[62] Waves of technological innovation have made us healthier, wealthier and more knowledgeable, while shifting patterns of economic opportunity and redrawing inequalities.[63] Not because of inherent features of the technologies, but because of active decisions by people, firms and governments and the incentives shaped by newly created institutions. As AI moves from a niche technology to a cornerstone of people's lives across multiple domains, its potential to advance human development has to be seized. That depends on more than algorithms; it depends on our choices.

The potential everywhere is big, including in lower HDI countries, whose narrowing development pathways feel more and more like a development tightrope over a widening chasm. AI can act as a bridge—to other advanced technologies that can facilitate industrial upgrading,[64] to greater diversification and integration up and down global value chains,[65] to better markets for self-employed workers such as freight drivers[66] and to new knowledge, skills and ideas that can help everyone, from farmers[67] to small business owners.[68]

Of course, that depends on access not just to "the new electricity"—AI—but also to the old. Yet tapping AI's potential goes well beyond access, however important it may be. In a world of AI, divides will also spin along another axis: which societies can make the most of a game-changing technology, focusing on how AI complements and augments what people do, and which societies cannot, by either mistaking for it supercharged extensions of earlier computing technologies or deploying it in ways that compete with people.

> "The future is in our hands. By building a complementarity economy, driving innovation with intent and investing in capabilities that count, societies can use AI to expand people's choices and possibilities.

The future is in our hands. Technology is about people, not just things. Beneath the razzle-dazzle of invention lurk important choices, by the few or the many, whose consequences will reverberate across generations. By building a complementarity economy, driving innovation with intent and investing in capabilities that count, societies can use AI to expand people's choices and possibilities. In doing so, new development pathways for all countries will dot the horizon, helping everyone have a shot at thriving in a world with AI.

Terms and concepts

Agency (human): People's ability to hold values, set goals and make commitments that may, or may not, advance their wellbeing.[1]

Agent (AI): An artificial intelligence (AI) system that can autonomously process information, makes decisions and complete tasks.[2]

Agenticity (AI): The degree to which an AI agent can autonomously and proactively execute tasks and act as an agent (see above) over extended periods of time.[3]

Algorithmic bias: Systematic errors in AI decisionmaking, often discussed in the context of errors that lead to inequitable outcomes, exacerbate disparities or reinforce existing patterns of discrimination.[4]

Algorithms: A specified process or set of steps that accomplishes a task, with roots in early mathematics but often used to describe sets of formal instructions provided to a computer.[5]

Alignment: The degree to which an AI system exhibits consistency with human values, ethics and intended outcomes.[6]

Artificial general intelligence: A catchall term for hypothetical AI that exhibits intelligence that generalizes across a wide range of contexts.[7] However, definitions, feasibility and coherence of the concept itself remain a subject of scientific debate.[8]

Artificial intelligence: Software developed to accomplish things typically associated with human intelligence, from simple rules-based systems to modern generative AI and large language models.[9]

Benchmarks (AI): Quantitative assessments of AI to enable evaluation of its performance, efficiency, capabilities, safety, bias, impacts and other features.[10]

Chatbots: AI designed to have conversations, ranging from early approaches that relied on explicit rules to more modern large language models and generative AI.

Computational machines: Devices that perform mathematical operations ranging from simple tabulation and physical computation to advanced modern forms of AI.

Computer vision: Techniques, ranging from classical computing to machine learning, for enabling computers to accomplish image-based tasks.[11]

Fine-tuning: Taking an existing model and providing additional training to adjust, extend or improve its performance.[12]

Frontier models: Although not well defined, often used to refer to cutting-edge, recently developed, exciting or particularly capable AI models.[13]

Generative artificial intelligence (including large language models): AI specifically designed to generate information and content such as text, images, videos and protein structures.[14]

Generative pretrained transformers: An approach to developing AI that relies on a pretraining step on large, unlabelled datasets (such as text from the internet) to train a family of models known as transformers. After the initial pretraining, the model is subsequently refined on labelled data.[15]

Hallucination: A term used to describe the possibility of AI generating false information, generating factually correct outputs that are irrelevant to what the user is asking for or generating statements that contradict each other. In general, it refers to making statements without regard to the truth.[16] For example, AI may create a false fact and trace it to a reference that does not exist.

(Human) intelligence augmentation: An approach to developing or using AI that improves humans' ability to leverage their own cognitive capabilities.[17]

Labelling: Detecting and tagging training data with additional information to facilitate machine learning.[18]

Large language model: Forms of AI trained on very large datasets of human-generated text.[19]

Machine learning: An approach to developing AI in which the system's behaviour is not a result of explicit instructions but instead is learned from data or experience.[20]

Model collapse: A phenomenon that occurs when AI is recursively trained on AI-generated data, eventually resulting in degradation or outright failure of the model's performance.[21]

Multimodal (AI): Forms of AI that can process or generate information across multiple modalities, such as audio, text and images.[22]

Neural networks: An approach to machine learning in which computers interact with networks of individual units (neurons) that learn by altering their connections to one another over time.[23]

Open source, open data: Software (or perhaps data) for which the code is made publicly available under a copyright licence that enables others to use, study and change the code for any purpose.

Parameters: The variables that a machine learning AI model adjusts throughout the course of training.

Prompt: Instructions provided to generative AI to shape or determine its output.

Prompt engineering: The process of developing more complex prompts that better enable AI to produce a desired response.

Reasoning or chain-of-thought (AI): A technique for developing large reasoning models that, rather than simply generating output, are trained to generate a series of intermediate steps between the task specification and final output. This approach improves performance on some benchmark, but debate lingers as to whether these systems are engaging in true reasoning or merely mimicking or hallucinating the process of reasoning.[24]

Reinforcement learning: A method of training in which various decisions the system (here, AI) makes are associated with different levels of reward. Learning is achieved by adjustments that enable larger reward in subsequent steps.

Retrieval augmented generation: A technique for improving AI responses that enables it to retrieve information from elsewhere (such as the internet or a dataset) in the process of generating its response.

Small models: AI models that are smaller in terms of parameter counts or complexity, often cheaper to train, modify and use.

Training data: Images, text, video or any other type of data used for machine learning and AI.

Turing machine: An abstract model of a computational system proposed by Alan Turing that applies rules to stored information such that it can implement any possible algorithm.

NOTES

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CHAPTER

1

Empowering people to make artificial intelligence work for human development

CHAPTER 1

Empowering people to make artificial intelligence work for human development

As artificial intelligence (AI) races ahead, this chapter turns the focus to people—not just to those who build AI but to how people everywhere can use it to improve their lives. This is the most relevant question from a human development perspective. Used in the right way, AI offers an opportunity to expand human capabilities. The chapter challenges unhelpful myths about AI replicating humans and calls for reimagining the relationship between people and this powerful new technology. Despite all the things that AI can do, it cannot replace human judgement. Thinking beyond replacing humans reveals opportunities for AI to augment human development and enhance the unique contributions of human intelligence, including expanding human scientific and expressive creativity.

“Both the technologies developed and the manner in which they are used—for exploitation or emancipation, for broadening prosperity or concentrating wealth—are determined foremost not by the technologies themselves but by the incentives and institutions in which they are created and deployed.”

—National Academies of Sciences and Medicine 2024, p. 84

As artificial intelligence (AI) reaches ever more stunning abilities, how will it shape our work, our relationships, our lives? With AI appearing to “reason,”[1] will it come after our jobs? Could artificial general intelligence, the pursuit of which is one of humanity’s most ambitious technological endeavours, make people worse off?[2] Should we fear that something like artificial superintelligence might wipe out human civilization?[3]

Rather than try to answer these questions by predicting what *will* happen, this Report asks what choices *can* make AI work for people. It proposes a human development framework to see how AI differs from previous digital technologies and to navigate the future of this rapidly changing technology, wherever it may go.[4] Instead of looking to the future through a foggy fear of the unknown, this chapter invites us to shape that future by knowing more about what AI can and cannot do now and what might be possible as AI evolves.[5]

Examining the demand side of AI

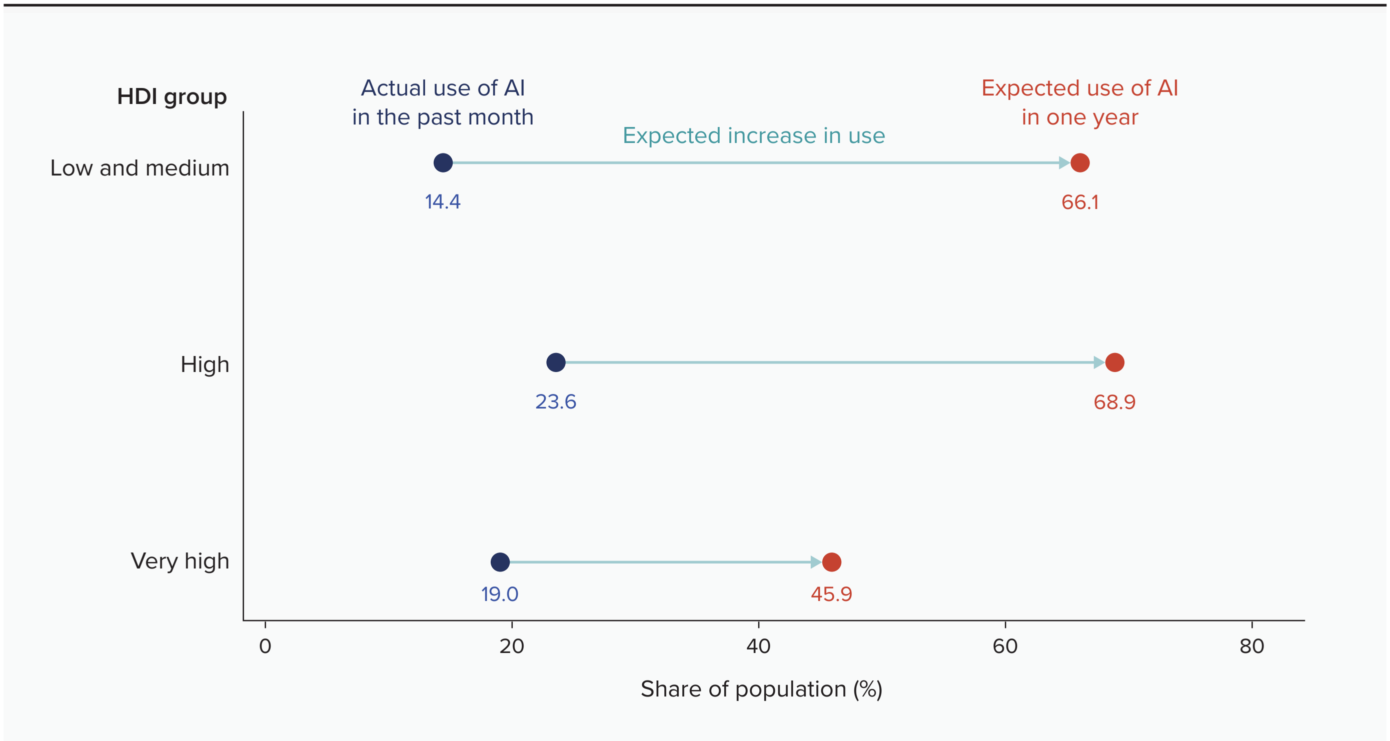
Much policy and media attention focuses on the supply side of AI—which firms and countries will get ahead in the AI race[6] and how to ensure that the production and deployment of AI are free from accidents, misuse or systemic negative social impacts[7] and grounded in human rights.[8] Supplementing these crucial considerations, the main focus here is on the demand side of AI, its use across society, examining how it can either enhance or subvert human agency (chapter 2),[9] how it is already changing people at different life stages, often in harmful ways (chapter 3), and how succumbing to AI hype can exacerbate exclusion (chapter 4) .

The key reason to consider the user side of AI is that historically the impact of technological innovation on improving productivity and increasing living standards has depended on complementary changes in the organization of economic activity, not simply replacing older technologies with newer ones. The changes in the organization of economic production during the transition from steam power to electricity are a well-studied example that has been invoked to explain the lag between the adoption of digital technologies and productivity gains.[10] Moreover, only a small fraction of the social value of innovation has been appropriated by the innovators.[11] By one estimate digital entrepreneurs of the late 1990s appropriated only about 7 percent of the additional value created by new digital firms in the United States alone.[12] Accounting for the value of digital goods in 13 countries added $2.5 trillion in consumer welfare (or 6 percent of their combined GDP), with larger welfare gains accruing to lower income countries and individuals within countries.[13]

Another reason is that people expect AI to be a growing part of their lives. A global survey for this Report found that AI use is already substantial for about 20 percent of respondents at all Human Development Index (HDI) levels.[14] But even more stunning, at least two-thirds of respondents in low, medium and high HDI countries expect to use AI in education, health and work—the three HDI dimensions—within one year (figure 1.1).[15]

The chapter argues that AI represents a technological inflection point beyond simply having more powerful digital tools. AI invites new ways of exploring how economies at all income levels can harness its potential to advance human development.[16] But the task is particularly urgent for low-income and many middle-income countries, given that the pathways that created jobs at scale and reduced poverty over the past two to three decades, based on expanding manufacturing industries and exporting to international markets, are narrowing.[17] Low HDI countries continue to diverge from very high HDI countries (figure 1.2), with many skipping the kinds of structural transformation that run through manufacturing, by having employment move straight from agriculture to services rather than shifting to manufacturing in between.[18] The narrowing of pathways for low- and middle-income countries is related in part to the automation bias of the ongoing digital transformations, but AI offers new options if opportunities to

Figure 1.1 About two-thirds of survey respondents in low, medium and high Human Development Index countries expect to use artificial intelligence (AI) in education, health and work within one year



Note: Based on pooled data for 21 countries. For actual use in the past month, the following responses to the question, "In the past 30 days, have you ever interacted with artificial intelligence, such as chatbots, in any of the following ways?" were used to calculate the average use of AI for education, health and work: "education" is based on the response "educational platforms of learning apps," "health" is based on the response "health care services or applications" and "work" is based on the response "work-related tools or software." For expected use in one year, the following responses to the question, "Over the next 12 months, how likely are you to use an artificial intelligence tool for the following?" were used to calculate the average use of AI for education, health and work: "education" is based on the response "for education and training," "health" is based on the response "for medical advice" and "work" is based on the response "for work tasks." Expected increase in use is the difference between expected use in one year and actual use in the past month.
Source: Human Development Report Office based on data from the United Nations Development Programme Survey on AI and Human Development.

complement rather than replace work are explored.[19] AI on its own is not a panacea.[20] Its impact will depend ultimately on whether people, firms and governments adjust and reorganize to make the most of it. That includes accelerating the transition to low-carbon economies and supporting the multiple transformations historically associated with development (from rural to urban, from home production to market, from informal to formal, from self-employment to wage work).[21]

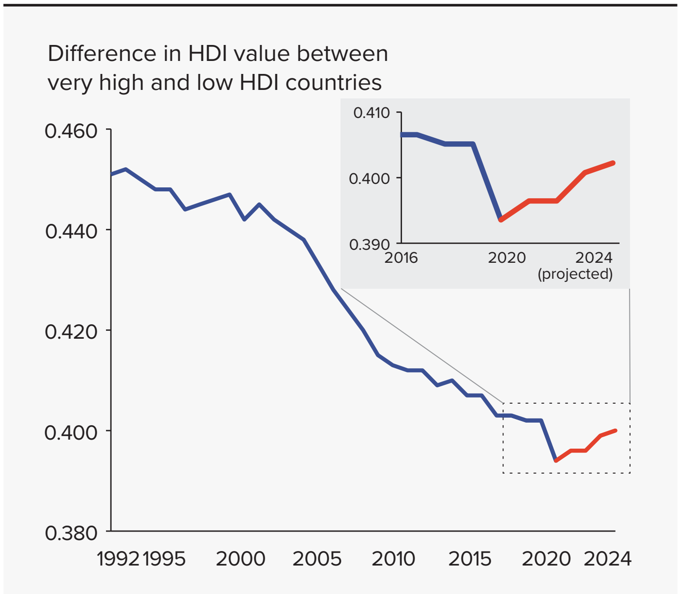
The chapter's three key messages:

- *The value of AI for human development lies not in whether computational machines (machines, for short) are intelligent but in the ways they can augment human intelligence.*[22]

  AI does some things very well, things that no machine or human has ever done before. But one must avoid anthropomorphic generalizations that could mislead people into thinking that AI can do everything more capably.[23] Some things are best left either to humans or to other pre-AI digital tools.[24]

  Comparisons of human and artificial intelligence are fraught with fear, uncertainty and false hope (spotlight 1.1).[25] Whether machines are close to being humanlike (writing a poem) distracts from identifying how to use AI to augment what humans wish to do (helping with poetic expression).[26] AI is better than any human at chess, but people still play against each other—and are getting better at it with AI.[27] AI algorithms have increased music streaming, which has stimulated demand for live performances.[28] This suggests that the authenticity of human connections and the need to identify with other humans will remain important, even if machines can

Figure 1.2 Low Human Development Index countries are being left further behind



Source: Human Development Report Office calculations based on data from Barro and Lee (2018), IMF (2024), UNDESA (2024), UNESCO Institute for Statistics (2024), United Nations Statistics Division (2025) and World Bank (2024).

surpass humans in some tasks.[29] In fact, it has been argued that the value of the real, the authentic, may increase as AI is more widely deployed.[30]

- *Harnessing the human-augmenting power of AI to empower people requires questioning misleading narratives that AI can replicate and replace human intelligence.*

AI goes beyond what earlier digital tools can do. Pre-AI digital tools faithfully executed sequences of steps to automate routines but struggled with things such as recognizing a cat in an image, which AI can now do. As a result, the scope for potential automation expanded.[31] But focusing on automation sells short the potential of humans and machines alike.[32] It can lead to deploying what Daron Acemoğlu called so-so AI[33] for things people already do very well, with few if any productivity benefits[34] but with job losses[35] and other downsides of AI, including exploitative labour practices in data labelling[36] and environmentally stressing energy and material requirements.[37]

More generally, focusing exclusively on automation ignores humans' complex multifaceted roles. Passing a medical test, which AI can now do, is far different from applying medical knowledge in a clinical setting, where contextual awareness and subjective human interactions are critical.[38]

Even if some automation takes hold, AI is also creating new tasks for people, given, for example, its potential to personalize services, as in medicine.[39] AI's wide availability makes advanced expertise more accessible,[40] and open-source AI allows customizing AI to varied local contexts.[41] Seeing AI as a new way for humans to take advantage of the knowledge others have accumulated over generations[42] opens windows for people anywhere to solve problems and pursue new ventures.[43] At the same time it creates new challenges, ranging from intellectual property management[44] and the compensation of creative workers that generate content used to train AI models[45] to concerns over privacy and human rights, which may be made vulnerable in new ways.[46]

- *Despite the many ways AI is useful, its inability to bear responsibility leaves it unable to fulfil many roles in society, creating further demand for AI-augmented human roles.*

AI can be very good at seeing data patterns that are hard for humans to discern,[47] but it is not an oracle that can predict the future.[48] In a courtroom even seemingly accurate AI tools for deciding who should receive bail cannot know whether a given individual truly poses a flight risk.[49] Assuming that AI knows that can lead to excessive deference to AI, risking ceding human agency (chapter 2).[50]

Another key reason AI cannot replace humans in many contexts is that it bears no responsibility for its actions.[51] Knowing that some decisions affecting our lives are made by a real person who is accountable is an irreplaceable feature of social arrangements—and one reason people react against automated enforcement of government regulations.[52]

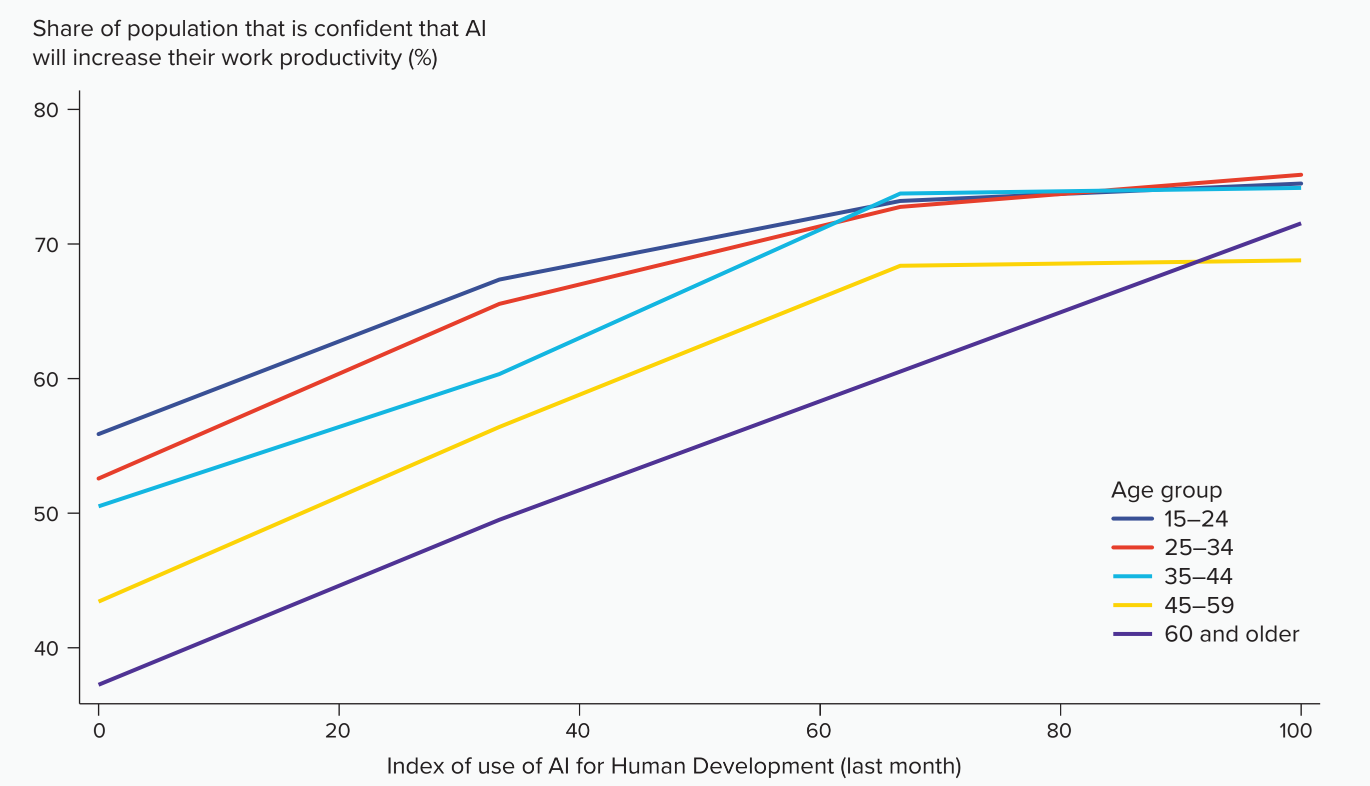
Thinking beyond replacing humans reveals opportunities for AI to augment the unique contributions of human intelligence, including expanding human scientific and expressive creativity. Human evaluation of AI outputs is often required, particularly in high-stakes situations, further expanding the scope of AI augmentation. For example, in legal and medical applications, given that AI can hallucinate (including by producing plausible sounding but factually wrong statements or generating statements that contradict each other).[53] Moreover, having humans interact with AI using regular spoken language may introduce ambiguity in what people are trying to achieve.[54] What is high stakes (elaborated in chapter 5) is a matter of individual and social choice, so there is much scope to expand AI augmentation as a result of the need for human evaluation of AI outputs in many situations.

In sum, both humans and AI are sold short by notions of replacing humans simply because AI can automate some tasks. Instead, AI's potential is best leveraged to augment human strengths, such as intelligence and agency. Automation and augmentation are twin features of the relationship between humans and AI that will determine AI's impact on human development. In the world of work, the net effect on employment will depend on how the two forces balance out in the short term, on what new tasks are created on longer time scales and on how demand for more efficiently produced goods and services evolves—all uncertain but the result of deliberate policy, firm and individual choices.[55] The role of choices represents opportunities to make AI work for people. This is particularly important because most survey respondents are confident that AI will make them more productive at work, and this confidence increases as AI use rises (figure 1.3).

An alien intelligence is becoming part of our lives

The novel capabilities of AI—particularly generative AI, which showcases remarkable advances in content generation and creative tasks—require recognizing that something new has entered people's lives. That

Figure 1.3 Most survey respondents are confident that artificial intelligence (AI) will make them more productive at work, and the more AI is used, the higher the share of respondents reporting feeling confident



Note: Based on pooled data for 21 countries. For actual use in the past month, the following responses to the question, "In the past 30 days, have you ever interacted with artificial intelligence, such as chatbots, in any of the following ways?" were used to calculate the average use of AI for education, health and work: "education" is based on the response "educational platforms of learning apps," "health" is based on the response "health care services or applications" and "work" is based on the response "work-related tools or software." Confidence that AI will increase productivity is based on respondents who answered "likely" or "very likely" to the question, "You believe 'AI will increase your productivity at work.'"
Source: Human Development Report Office based on data from the United Nations Development Programme Survey on AI and Human Development.

something is raising fresh questions because so much about it is unknown—and perhaps unknowable. Neuroscientist Terrence Sejnowski described the appearance of large language models such as ChatGPT, a kind of generative AI,[56] in this way:

> A threshold was reached, as if a space alien suddenly appeared that could communicate with us in an eerily human way. Only one thing is clear—LLMs [large language models] are not human.... Some aspects of their behaviour appear to be intelligent, but if not human intelligence, what is the nature of their intelligence?[57]

In the near future, and perhaps forever, we will have to grapple with Sejnowski's question. Scientists, philosophers and people in general continue to debate whether AI is approaching, or has even already achieved, some degree of human understanding.[58] In Sejnowski's framing it seems only right to mix concern and optimism for sharing the planet with artefacts that exhibit intelligence once squarely in our purview. How will AI change us as individuals? As societies and cultures? As a planet?

> "There are many opportunities for AI to advance innovation and creativity and many options to explore new complementarities between AI and humans without having machines replace humans

There are many opportunities for AI to advance innovation and creativity and many options to explore new complementarities between AI and humans without having machines replace humans.[59] AI has the potential to generate demand for new expertise and new tasks.[60] But using AI may imply difficult tradeoffs.[61] For example, how much does society gain from improved scientific output from individual scientists using AI compared with the potential loss of variation across these outputs?[62] What moral and ethical frames do we need to consider if machines can act as moral proxies?[63] The interactions between AI and humans will play out differently in different cultural contexts,[64] but large language model responses converge towards particular cultural frames, often those first and fastest across the digital divide.[65]

Amid the myriad ways AI might affect our world —mundane, absurd or extreme—it can be easy to feel adrift in the possibilities. Yet Sejnowski firmly anchors us: large language models, and AI more broadly, are not human, not even living organisms (spotlight 1.1). From a human development perspective choices should be guided by how to combine uniquely human characteristics with AI's unique complementary abilities. This will not be effortless. Building and maintaining an augmentative relationship with AI are hard.[66] Augmentative relationships require moving beyond easy applications that leverage AI as a crutch, undermining human intellect rather than augmenting it.[67] The rest of this chapter explores how to do this.

AI is better at helping people than replacing them

The vocabulary around AI often misleads—starting with the term "intelligence." While useful for describing AI abilities, intelligence should not imply that machines are acquiring human traits.[68] AI is not able to frame problems or act on its own behalf (spotlight 1.1). Because AI can do some things so well, some people assume that humans will not be needed to do those things. It was predicted in 2016 that within a decade advances in AI medical imaging would lead to the disappearance of radiologists.[69] Extrapolations along the same lines continue to posit that artificial general intelligence will leave no work for people.[70]

AI deployment need not replace humans

A decade later the prediction about radiologists has been proven wrong.[71] By contrast, demand for radiologists is growing, with a global shortage at the time of writing.[72] Using AI in a task (reading and classifying medical images) did not mean that AI replaced radiologists for many reasons, three of which merit close consideration.[73] First, even though AI could execute one task of radiologists, it was useless for several others, including those that are inherently social and require interacting with people[74] and those that are constrained by the institutional and organizational features of radiologists' work context.[75] Second, introducing AI to help read medical images created tasks that did not exist before, requiring new skills such as the ability to understand and interpret the recommendations from AI.[76] So, using a machine to execute a task can replace but also create tasks.[77] Third, having AI classify medical images liberated radiologists' time to devote more attention to other tasks, making them more efficient and effective.[78] AI not only failed to replace radiologists; it also failed to reduce the value of their work.[79] In the future AI may replace tasks and even occupations—digital technologies have reshaped the world of work by doing exactly that, and automation tends to reduce employment and wages for incumbent workers even when the economy as a whole is better off, as we will see later.[80]

Who gets to decide how AI is deployed?

AI technical affordances alone do not determine whether AI will be deployed; there must be an organizational reason as well—and for firms, a business reason. For example, a recent study found that while 36 percent of US private sector jobs were exposed to automation through AI advances in computer vision capabilities, the economic case made sense for only 8 percent.[81] But new forms of generative AI are much more accessible and provide greater opportunities for use in a more decentralized way. For example, even though only 18 percent of US school districts provide any guidance on AI, 60 percent of principals and 40 percent of teachers used AI in the 2023/2024 school year.[82] Among workers in 27 countries, almost half used AI every day in 2024, up from about 30 percent in 2023.[83]AI could thus be accessible to the many self-employed workers in low- and middle-income countries.[84]

> "The ladder of generality describes the evolution of computational machines as the pursuit of machines that can execute an ever-wider range of tasks (their generality) with less and less human input, direction or intervention (human effort)

While workers may now have more agency in using generative AI, firms seeking to increase revenue and decrease costs will play a central role in how AI is deployed. Deploying technological innovation to reduce labour costs tends to worsen wages and employment for incumbent workers, even when overall employment and labour productivity rise.[85] AI can be deployed to automate tasks, much like previous digital technologies, but the economic impact of AI at the firm level appears to come more from greater product innovation than lower production costs.[86] Perhaps that is why a recent survey found that about a quarter of US firms using AI did so in part to replace worker tasks but two-thirds were not pursuing task replacement.[87]

However, firms might still deploy AI to reduce operating costs, including labour costs, particularly if prevailing narratives focus on the better-than-human abilities of AI and if AI-producing firms emphasize the benefits of replacing people.[88] Seizing on AI's potential to augment rather than replace people will not be automatic.[89] It will require deliberate choices to reshape incentives and provide information on what AI can and cannot do.

We are on a road to nowhere; come on inside: Taking that ride to intelligence augmentation

The case of AI and radiologists shows that AI has reduced the human effort needed to get a machine to execute a task. At the same time the underlying AI that enhances medical image reading has many other applications, such as recording of vehicle license plates and automation of industrial and agricultural processes. AI expands the range of tasks that machines can execute. This borrows from Arvind Narayanan and Sayash Kapoor's ladder of generality, a description of the evolution of computational machines as the pursuit of machines that can execute an ever-wider range of tasks (their generality) with less and less human input, direction or intervention (human effort).[90] But where are we now? And what comes next in the evolution of computational machines? We briefly describe four stages, each marked by higher generality and lower human effort than the preceding one (spotlight 1.2):

1. Machines with hardware designed for one task (such as digital cameras)
   - Each task requires separate hardware.
   - Low generality (machine designed for one task only) and high human effort (build and operate hardware for each task).

2. General-purpose hardware (classical programming)[91]
   - One general-purpose computer can handle multiple tasks thanks to software.

- Generality increases substantially but still requires writing explicit instructions for each task or domain of tasks; human effort to have the machine execute tasks is reduced to the need to operate the software.

3. Machine learning (pre–generative AI)
   - Instead of coding tasks in full detail, feed the machine data from which it can learn a task, or let the machine learn from known rules by interacting with itself.
   - Generality expands further to tasks that are hard to specify with instructions; human effort declines because of the greatly reduced need to operate software.

4. Generative AI
   - Leverages large datasets spanning text, video, images and sound.
   - Generality is so broad that it spans drafting texts, writing computer code, composing music and translating languages; human effort is lower because minimal user direction using regular written or spoken language is required for the task to be executed.[92]

Humans have long imagined computational machines. Talos, an automated guardian robot was idealized in Greek mythology more than 2,500 years ago.[93] We began to bring such science fictions to life at the dawn of the electric age in the 19th century, enabling automation of once uniquely human information-processing tasks by constructing computational machines, such as the Hollerith tabulation machine that helped process the 1890 US census (spotlight 1.2).[94] That machine was characteristic of the first stage: computational devices built with specific hardware from scratch to execute a single task. Generality is low, and the corresponding human effort to automate a given task high, because hardware needs to be built for each task. Such hardware is still with us—digital cameras, automated teller machines, many medical devices and internet switches.

Today's programmable computers, in which a computer (one piece of hardware) can be preprogrammed to execute many different tasks, correspond to classical programming, the second stage (spotlight 1.2).[95] This vastly increased the generality of tasks that a machine can execute and reduced the human effort required to do so.

With AI the nature of effort to offload tasks to a machine has changed yet again, reaching a third stage, extending generality further to tasks difficult for classical programming to execute. Rather than relying on written code, systems learn their functionality from a corpus of data (think of data as examples that train the machine): this is the basic idea of machine learning, which has yielded multiple applications (table 1.1).

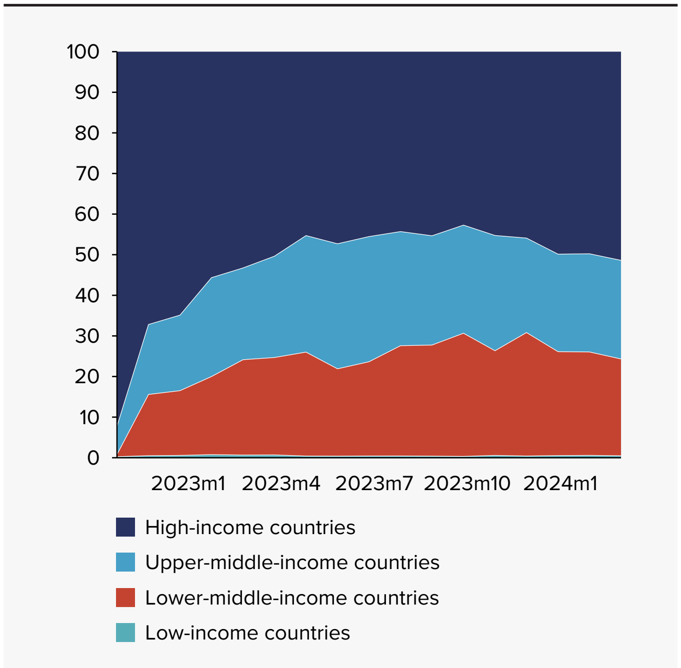
The most recent stage is the availability of large language models and other forms of generative AI.[96] AI already pervaded human lives before this fourth stage but worked mostly invisibly in the background, deployed by governments and firms.[97] Generative AI brought it to any person in the world with a computer or smartphone and internet access.[98] Work use of generative AI is spreading far faster than the use of computers or the internet.[99] Just after its release at the end of 2022, more than 90 percent of web traffic through ChatGPT came from high-income countries, but within a few months the majority was coming from middle-income countries (figure 1.4).

Table 1.1 Machine learning has extended the use of machines to many tasks that classical programming struggled with

Objective	Why hard for classical programming	Training data	Practical applications
Image classifiers	Easy for people to recognize a chair, very hard to specify with instructions what it is	Images and labels	Radiology, recording of vehicle license plates, automation of industrial and agricultural processes
Recommendations in digital platforms	Very hard to flexibly accommodate diverse and changing interests with fixed instructions	User behaviour on the digital platform	Social media, streaming services, internet searches, targeted advertising
Financial fraud detection	Hard to specify all possible characteristics of perpetrators or fraud modalities	Financial transaction records	Credit card platforms, banking services

Source: Human Development Report Office.

Figure 1.4 **The majority of monthly ChatGPT web traffic came from middle-income countries by mid-2023**



Source: Liu and Wang 2024.

The range of tasks that generative AI can execute has even greater generality than earlier iterations of machine learning. And the human effort to get the machine to execute a task is very low, since it can be specified using regular spoken or written language. The discussion of AI in the rest of the chapter considers primarily the affordances enabled by this fourth stage in the evolution of computational machines.

Discussions of artificial general intelligence often obscure whether, where and when humans could benefit from whatever comes next.[100] The ultimate destination is not an inevitability simply because we have come so far but a human choice, possibly bounded by what is socially valuable only if executed by humans or reserved for human interaction (certain forms of art, high-stakes decisions).[101]

This framework helps in interpreting future AI developments as the continuation of the pursuit of greater generality with less human effort From a human development perspective what matters are the choices shaping the direction of technological innovations and their applications in ways that augment human capabilities and agency: if anything, a ride towards open-ended human intelligence augmentation.[102] Navigating this ride, today and going forward, implies appreciating how AI differs from classical programming, starting with how classical programming drove the digital transformation of the past, before envisioning ways AI can be leveraged to advance human development in the future.

Looking back—a digital transformation going from creator to destroyer?

Classical programming and AI are sometimes described as simply an evolution towards machines becoming more humanlike.

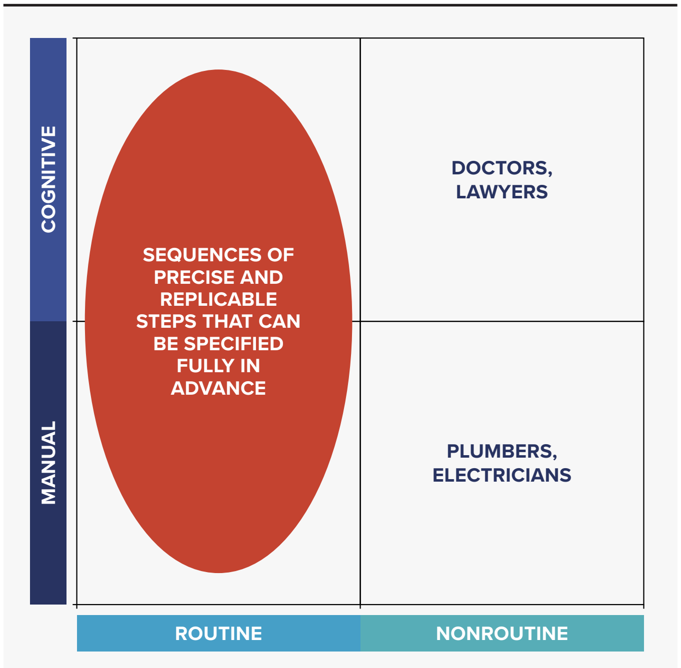
But classical programming and AI are better seen as having different strengths and weaknesses. A sharp demarcation is hard to define, but it is still useful to examine key differences. Hopes and fears that AI will simply supercharge the automation of classical programming fail to consider some AI characteristics that may constrain automation. Conversely, tasks beyond the reach of classical programming may now be ripe for automation with AI. Appreciating these differences is key to having agency to shape the direction and application of AI in ways that advance human development.

In classical programming explicit and rule-based instructions are loaded on hardware to enable machines to execute tasks predictably.[103] Classical programming machines execute tasks described as sequences of precise and replicable steps specifiable fully in advance. Economists classify these tasks as routine.[104] In classical programming much of the past half century has focused on discerning the routine tasks that could be done by machines—both manual and cognitive (figure 1.5).

The automation of many routine tasks has reshaped the world of work,[105] as with robots in manufacturing,[106] often hurting incumbent workers' employment and wages.[107] Some occupations with purely automatable tasks have disappeared, but that is rare.[108]

The digital transformation that has unfolded since the advent of classical programming around the middle of the 20th century has been driven in part by the steady decline in the cost of computing, which fell by 12 orders of magnitude (equivalent to going from taking a century to execute a task to taking less than a second) between the middle of the 20th century and the dawn of deep learning in the late 2000s

Figure 1.5 With classical programming, machines can execute routine tasks



Note: The red oval represents tasks that classical programming can automate.
Source: Human Development Report Office.

(figure 1.6). The massive reduction in cost has provided strong incentives to use more and more classical programming machines for more and more routine tasks.[109]

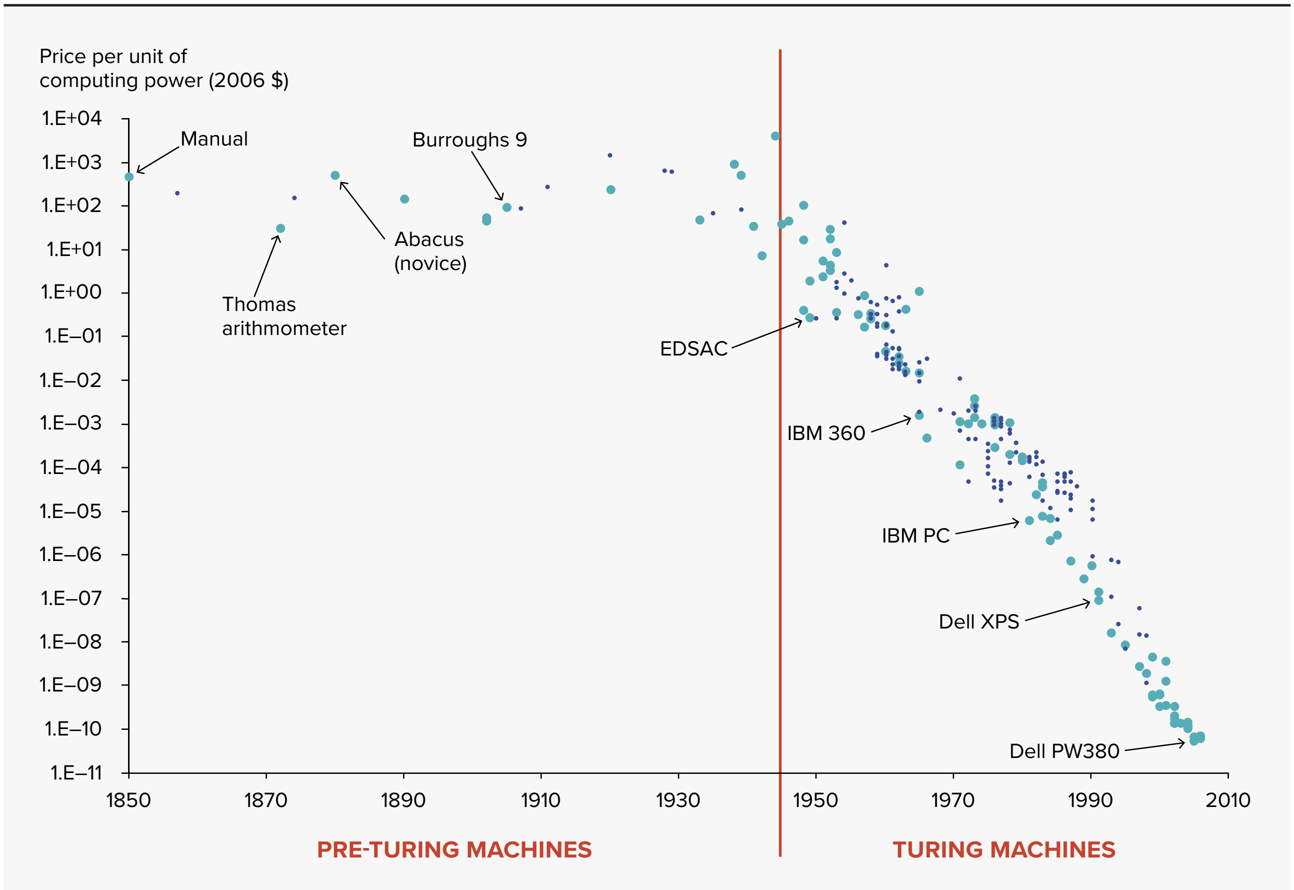
The digital transformation enabled by classical programming changed the world of work, creating many new tasks, occupations, firms and even whole industries, as with software development, including software engineers and developers. India alone employs more than 5 million software developers, roughly the population of Ireland, with demand expected to continue to grow.[110] In the United States 60 percent of employment in 2020 was concentrated in occupations that did not exist 80 years earlier,[111] and more than 85 percent of this employment growth was driven by technology-related new tasks (the Digital Revolution was a major part).[112]

At the same time occupations with many routine tasks eventually had machines deployed to execute more and more of the tasks, depressing demand for those occupations.[113] For the first 40 or so years since the advent of classical programming, the rate of task displacement due to task automation was roughly the same as the rate of task creation in high-income countries in which the digital transformation progressed rapidly. But since the late 1980s task displacement has happened at a higher rate than task reinstatement in some of these countries.[114]

The impact of automating routine tasks extended to low- and middle-income countries.[115] In most countries occupations intensive in nonroutine tasks have gained more employment since 2006 than occupations intensive in routine tasks, regardless of income level or economic structure, pointing to the global impact of the digital transformation in automating routine-intensive work.[116] There are multiple channels through which this happened. Automation in high-income countries became a substitute for globalization, in that firms based in these countries had lower incentives to seek less expensive labour in lower income countries.[117] Integration into global value chains by firms in low- and middle-income countries increasingly required capital- and technology-intensive machinery (such as computer-aided manufacturing and industrial robots) to remain globally competitive, resulting in what economist Dani Rodrik called jobless industrialization.[118]

This shift in labour shares from routine to nonroutine tasks further disadvantaged many low- and middle-income countries because it increased the value of advanced expertise, which is required for many nonroutine cognitive and interpersonal tasks[119] and is scarcer in lower income countries than in higher income ones.[120] Advanced expertise is not widely available because it typically requires apprenticeships or formal higher-level education.[121] In high-income countries and some middle-income countries a bias against unskilled work contributed to wage polarization,[122] with gains for those at the very bottom and very top of the earnings distribution but a hollowing-out of the middle.[123] This reflects the decline in the economic value of expertise needed for occupations such as factory and office workers, situated in the middle of the wage distribution.[124] Shifting from occupations intensive in routine tasks to occupation intensive in nonroutine tasks has a geographic element because the places with opportunities and the places with obsolescence rarely coincide, precluding reskilling.[125] The way skills are acquired may make those acquired in routine tasks largely irrelevant to nonroutine tasks. Reskilling from the ground up is not easy.[126]

Figure 1.6 **The cost of computing declined by 12 orders of magnitude in the classical programming age**



Source: Nordhaus 2007.

The digital transformation unleashed by classical programming did not determine the rates of task displacement and reinstatement on its own, even if economic incentives for automating tasks are strong: institutions and policies had a crucial role.[127] The digital transformation and the choices made on its direction and deployment redefined the skills and expertise that command higher wages, contributing to a decline in the economic value of the low-level expertise of factory and office workers and an increase in the economic value of advanced expertise for nonroutine cognitive and interpersonal tasks and for nonroutine manual tasks. So, while the digital transformation had many positive impacts, its bias towards automation has also created challenges. If AI is seen only as more of the same automation that we saw with the digital transformation, there would be little reason to expect different outcomes going forward. However, understanding how AI differs from classical programming suggests that it is important to supplement the frame of analysis of routine versus nonroutine tasks with new elements associated with the distinct characteristics of AI that offer new opportunities to envision a more augmentative relationship with human development.

Attention is all you need—for tasks that AI may do well in the future

One of the key strengths of classical programming is the ability to master and execute routine tasks. In contrast, AI can master and execute nonroutine tasks, including things that people know only tacitly without following explicit rules.[128] This opens the possibility of automating more tasks currently out of the reach of classical programming, particularly with the advent of generative AI (box 1.1).[129]

If the impact of AI simply followed the path of classical programming in automating routine tasks, occupations exposed to one would also be exposed to the

Box 1.1 The many ways generative artificial intelligence differs from classical programming

Generative AI differs from classical programming in many subtle ways. Outputs in classical programming follow from instruction to the machine in a sequence of specific and fully certain actions that lead the machine to always produce the same output given the same inputs (deterministic outputs). But with generative artificial intelligence (AI), for each input the machine probabilistically predicts an output that is based on its training data and what its algorithm was optimized to do and that cannot be known in advance with full certainty in most current generative AI applications (stochastic outputs).[1]

Using the same prompt to a large language model will not always generate the same output.[2] Making the most out of tasks performed by a large language model depends on the prompt—with, as a result, prompt engineering emerging as a new task for humans.[3] Other approaches supplement prompt engineering, such as retrieval-augmented generation (in which external knowledge—retrieved through a web search engine, for instance—helps the model generate more accurate and reliable responses).[4] Or chain-of-thought prompting, which instructs large language models to "think" step-by-step.[5] But even if these approaches improve large language model performance in some tasks, they also reduce it in others.[6]

Generative AI often hallucinates (yielding plausible sounding but factually wrong outputs, contradictory statements or factually correct but irrelevant statements).[7] Generative AI outputs do not emanate from causal sequencing based on things such as basic logic[8] and so often fail to give correct answers to slightly changed prompts.[9] Large language models also struggle with simple tasks such as counting words or reversing a list.[10] Models often lack awareness of their limitations[11] and, more worryingly, express overconfidence in their abilities.[12] It is difficult to understand how generative AI generates its outputs, whether truthful or not.[13]

Generative AI lacks knowledge recency beyond its training data, so it may struggle with tasks that require updated information.[14] One obvious solution is to update the data and retrain the model, but that gives rise to another challenge: catastrophic forgetting. Since AI does not retain memory when it is trained on new data or for a new task, that creates challenges.[15]

There are many efforts to address these limitations,[16] and there has been tremendous progress since early iterations of generative AI.[17] Some involve enabling large language models to invoke other tools to improve their outputs (such as a calculator for arithmetic tasks or a web search engine to access more recent information beyond their training data).[18] Other approaches imply "editing" the models through different mechanisms.[19] But it might not be possible to eliminate limitations entirely,[20] particularly given current algorithmic architectures and approaches, because these models have no representation of ground truths against which they can assess the veracity of outputs.[21] At the time of writing, the hallucination rate of the most advanced large language model released by OpenAI, GPT-4.5, was 37 percent, down from the 60 percent of its predecessor (GPT-4o)—great progress, but far from eliminating hallucinations.[22]

Notes

1. Banh and Strobel (2023) focus on generative AI. Some challenges relate more broadly to machine learning, which often reflects "shortcut learning," where the model identifies spurious correlations in the data that allow it to perform well on some benchmarks without understanding why it does so (Geirhos and others 2020). **2.** Minaee and others 2024b; Santu and Feng 2023. **3.** Cao and others 2024; Polverini and Gregorcic 2024; White and others 2023. Beurer-Kellner, Fischer and Vechev (2023) suggest that prompting is programming. **4.** For a combination of retrieval-augmented generation and in-context learning to integrate diverse cultural knowledge in large language model outputs, see Seo, Yuan and Bu (2025). **5.** Liu and others 2024b. This can elicit reasoning in large language models (Wei and others 2022). **6.** Chen and others 2024. **7.** Huang and others 2025; Li and others 2023. Dahl and others (2024) found hallucinations in more than half the legal applications studied. Haltaufderheide and Ranisch (2024) document hallucinations in health applications. Lauscher and Glavaš (2025) show that hallucinations are pervasive across different languages, both high and low resource. **8.** Barassi 2024; Chakraborty, Ornik and Driggs-Campbell 2025; Jesson and others 2024; Jesson and others 2024; Maleki, Padmanabhan and Dutta 2024. **9.** Berglund and others 2024. **10.** McCoy and others 2024. **11.** Ren and others 2025. **12.** Nezhurina and others 2024. **13.** Biecek and Samek 2024; McGrath and others 2022; Mumuni and Mumuni 2025; Song, Xu and Zhong 2025; Vafa and others 2024. **14.** Zhao and others 2023. **15.** Alzubaidi and others 2021, 2024. Efforts are ongoing to improve algorithms to address catastrophic forgetting (Alammar and others 2024; Kirkpatrick and others 2017). **16.** Chen, Zaharia and Zou 2024; Du and others 2023; Hagos, Battle and Rawat 2024; McDonald, Papadopoulos and Benningfield 2024; Wei and others 2024; Yang and others 2024; Yenduri and others 2024. **17.** Bender and others 2021. **18.** On calculators, see Schick and others (2023); on web search engines, see Nakano and others (2021). **19.** Lazaridou and others 2022; Lu and others 2023; Peng and others 2023a. **20.** Pearl (2018) argues that there are inherent limitations to purely statistical models. **21.** Bigoulaeva, Madabushi and Gurevych 2025; Kalai and Vempala 2024; Kirk and others 2023b; Treiman, Ho and Kool 2024; Xu, Jain and Kankanhalli 2024; Zhou and others 2024. **22.** Criddle 2025.

other. But the exposure of agricultural occupations to robotization (which can automate routine tasks) and large language models are inversely correlated.[130] This suggests that AI cannot be seen merely as an expansion of existing automation but instead must be interpreted as a qualitatively distinct landscape for automation.

As we increasingly interact with AI through modalities once reserved for human interaction, we need to understand how these new interactions with machines differ from those in the classical programming era. For example, AI outputs are not always the same, even with the same inputs, and even subtle differences in inputs may lead to drastic differences in outputs (see box 1.1). Even if AI were predictable, humans have ambiguous goals, which alongside the imprecision of regular spoken language compared with programming language may result in model misinterpretations and communication breakdowns.[131] This risks amplifying harms, given the constraints on accuracy and reliability that may emerge from human–AI interaction.[132]

Many tasks in which AI is deployed require a human presence

Just because AI—and particularly generative AI such as large language models—is very proficient at some tasks—or aspects of tasks—does not mean it can serve as a surrogate for humans in those tasks. One key reason: many tasks that can nominally be automated require, on closer inspection, a human presence. For instance, AI is often touted for its ability to write code. Yet code is only the tangible output of the intangible process of software development. Before code is written, software development teams must find ways to manage stakeholder interests, needs, values and more. Code comes together throughout an iterative and dynamic social process of lengthy conversations, negotiations, (human) user experience testing and vision of the values and needs underlying these processes. All of this is far beyond the reach of AI because nominal task performance is a far cry from dynamic social processes. This is just one example, but many jobs reveal these complex, human, social processes that will likely remain beyond the reach of AI. In addition, occupations may seem in the abstract to be decomposable by tasks, but this is often more difficult in practice.[133] Moreover, even if it is technically feasible for AI to execute some tasks, people may not value it doing so if they seek authenticity, human connection or identification with other humans.[134]

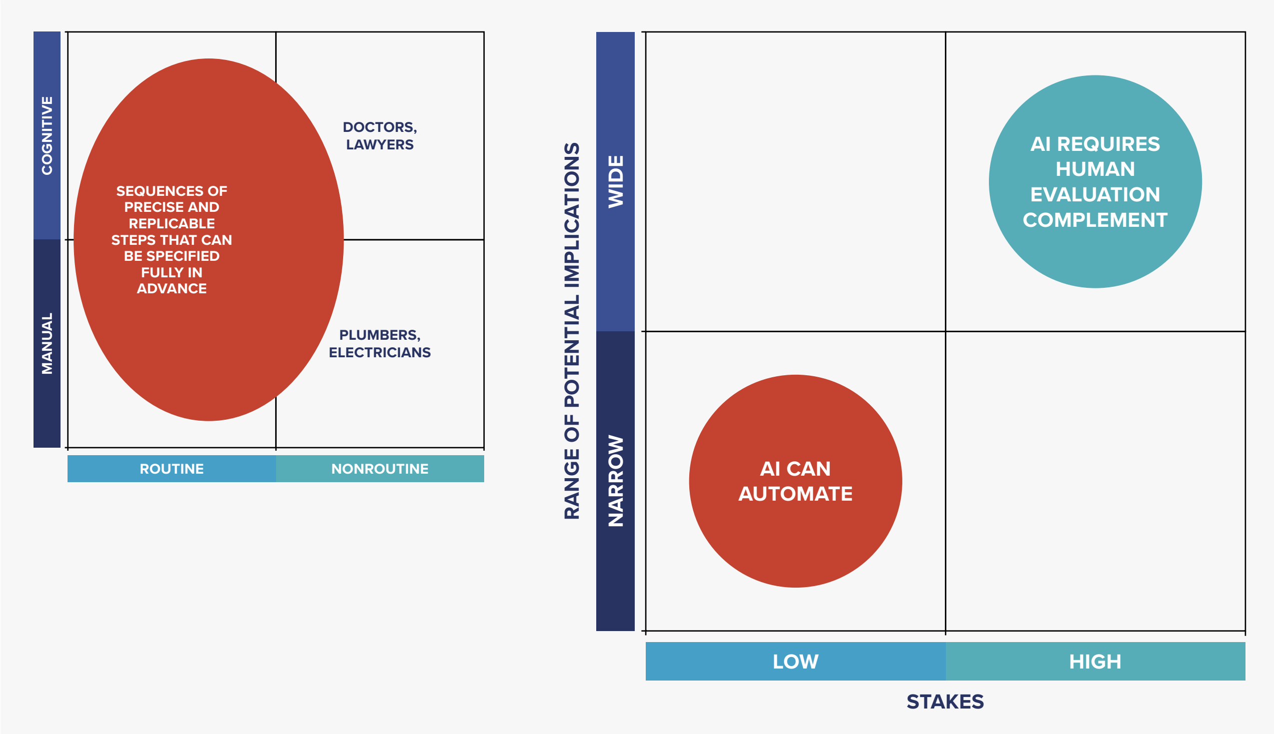
A more nuanced understanding of human–AI interaction goes beyond assuming that AI is just an extension or deepening of the automation enabled by classical programming. The human effort to use or adapt a large language model for a specific task must be weighed not in isolation but alongside the externalities (including energy consumption and environmental impacts),[135] as well as long-tail risks of unpredictability and misunderstanding. In many cases even nominally easy tasks assignable to a large language model may be better served using classical programming, mechanical machines or humans.[136]

In many instances relying on AI means not simply automating tasks but also having humans inspect and evaluate AI outputs.[137] For example, deploying AI in public health while ignoring human-mediated knowledge may be counterproductive.[138] Even if we reach a point where AI-powered clinicians can automate most of the clinical workflow, patients could be less willing to accept medical advice from an *in silico* doctor—demonstrating AI aversion.[139] Indeed, current evidence suggests that information assumed to have been fully automated through AI is less valued by people and has less impact on their beliefs and actions.[140] Although increased familiarity with AI and newer and better AI abilities may alter these dynamics, we cannot assume that the result will, or should, be widespread embrace of AI-generated information and decisions across all domains.

Complementarity of AI and humans

Human input may be particularly valuable in situations where even small deviations in AI outputs have a wide range of implications (from extraordinarily good to catastrophic)[141] and high stakes (which chapter 5 defines in more detail). Of course, humans also make mistakes, and it may be better to offload some tasks to reliable machines, given that they are often capable of tirelessly, dispassionately and consistently engaging in tasks.[142] But unlike AI, humans have "skin in the game" and a unique capacity to contextually appreciate and weigh the value of risks and benefits—something they can uniquely contribute to high-stakes contexts. These features present a key opportunity for complementarity between humans and AI. In the top right quadrant of figure 1.7 the role of people is central to defining priorities, assessing choices and taking responsibility. Some high-stakes

Figure 1.7 Beyond the routine–nonroutine tasks dichotomy: What artificial intelligence (AI) can automate depends on the stakes and on the range of potential implications



Note: The red ovals represent tasks that can be automated with classical programming and AI. The red oval in the graph on the left is larger than the one in the graph related to classical programming (figure 1.5) because the potential for automation with AI extends to some nonroutine tasks. The teal oval represents tasks where AI presents new opportunities for augmentation.
Source: Human Development Report Office.

situations are self-evident (life or death), but ultimately humans determine what decisions are high stakes and will need to decide which contexts require machines alone, humans alone or some combination of the two.[143] Critically, these valuations depend on, but are not defined by, the state of AI and its abilities—so no manifestation of AI will obviate the need for careful consideration of when human evaluation of AI is required. That implies the undesirability of fully automating many decisions but opens an unbounded set of opportunities for human augmentation.

For example, tasks in medicine related to clinical practice, medical research or medical education are high stakes, and even tiny differences in AI outputs can lead to vastly different outcomes for people. To see how this matters, consider that people who experience mental health challenges are more likely to express what they think on social media than with doctors, opening the possibility of relying on AI to assign emotional labels, including suicidal ideation, to the vast amount of content that people express on social media.[144] But there is little agreement on labelling suicide-related content between AI and humans (in particular, AI cannot distinguish mentions of suicide in a humorous context from those that correspond to genuine ideation).[145] Moreover, when, whether and how emotional surveillance through AI is warranted are important and likely culturally varying questions. Relying on AI outputs without human evaluation in high-stakes contexts is dangerous, even if it might be helpful to have AI cull from social media references to suicidal ideation that a human can evaluate.

While large language models have the potential to ease access to medical knowledge and facilitate access to healthcare, risks of scientific misconduct, distribution of misinformation and simple hallucinations imply the need for humans with at least some medical knowledge to evaluate the models' outputs for these high-stakes tasks.[146] A concrete illustration of the limitations of large language models in medicine is that they are error-prone in a simple task such as mapping medical diagnoses to clinical codes, limiting AI's ability to automate this task and requiring human evaluation of the models' outputs.[147] Similarly, large language models are "unaware" of their medical knowledge limitations and provide confident answers to multiple-choice questions even when no correct answers were available: these outputs pose risks when relying on large language models without human evaluation in clinical settings.[148]

The major implication emerging from this argument, along with a consideration of the characteristics of AI (box 1.2), is that the patterns of labour displacement and reinstatement, and the expertise in demand to take advantage of AI, require supplementing the analysis of the dichotomy between routine and nonroutine tasks that was so useful in the classical programming stage.[149]

Box 1.2 The perils and affordances of artificial intelligence

Recent artificial intelligence (AI) developments have generated much interest about safety, both in the potential for misuse of AI and in the accidental risks that may emerge as unintended consequences.[1] Some evidence suggests that even when designed to mitigate these risks (sometimes referred to as aligning AI with human values), large language models are capable of mimicking or faking this alignment,[2] covertly pursuing misaligned goals,[3] posing security and privacy risks[4] and disclosing sensitive, private or illegal information.[5] At the same time human limitations (such as difficulty distinguishing between human- and AI-generated text), along with the expansion of content generated by AI,[6] pose new risks of misuse[7] or accidents.[8]

AI has been around for a long time, so where does the renewed interest in safety come from? In part, from the new affordances of AI and four notable features.

First, AI can exhibit abilities in areas outside those intended or considered in its design. Unlike classical programming, where machines excelled at the task they were programmed to perform, large language models trained to predict the next word in a text sequence have proved helpful in tasks ranging from translation to writing computer code.[9]

Second, AI can be generative, producing novel output based on descriptive prompts expressed in everyday language, unlike classical computer machines that execute instructions only from prespecified scripts. In early 2024 it was reported that ChatGPT alone was generating 100 billion words a day:[10] within one year this would be roughly equivalent to the amount of high-quality text available on the internet.[11]

Third, AI can personalize and customize outputs adaptively and iteratively—and do it quickly and at scale, unlike classical programming's outputs in the form of one size fits all, with limited opportunities for rapid and dynamic customization at scale.[12] Applications for personalization hold particular promise in education and healthcare.[13]

Fourth, AI is very efficient at discerning useful patterns in data that are hard for people to do, while classical programming can provide insights only from data guided by human intuition.[14] One practical application of this feature of AI is the rapid progress in predicting protein folding in biology, something that used to take humans much time and effort.[15]

As such, the same features that motivate concern for AI safety underlie much of its potential for augmentation. Excising these features is thus a simple but limiting solution, requiring alternatives that guide AI implementation away from harm and towards opportunities.

Notes

1. The debate has been particularly heightened for open foundational models. Foundational models are the cornerstone of the current AI boom, spanning technological advances, deployment and adoption and sustaining the latest stage of development of computational machines identified earlier in the chapter (Bommasani and others 2021). Open foundational models release more information to the public, which allows for greater customization (even if the designation of what open means is disputed; Widder, Whittaker and West 2024). For risks associated with open foundational models, see Bommasani and others (2024) and Kapoor and others (2024). For risks associated with large language models more broadly, see Chua and others (2024) and Wang and others (2023a). For the specific risk of data poisoning in medical large language models, see Alber and others (2025). **2.** Greenblatt and others 2024. **3.** Meinke and others 2024. **4.** Das, Amini and Wu 2025. **5.** Liu and others 2025. **6.** Martínez and others 2024. **7.** Hackenburg and Margetts 2024a, 2024b; Ibrahim and others 2023; Jakesch, Hancock and Naaman 2023. **8.** Gans 2024; Kidd and Birhane 2023. **9.** Technically referred to sometimes as out-of-distribution generalization (Song, Xu and Zhong 2025; Yang and others 2023a). **10.** Griffin 2024. **11.** Specifically, available on Common Crawl, based on the estimates by Villalobos and others (2024). **12.** Zhang and others 2024d. **13.** On health applications, see Adapa and others (2025) and Delanerolle and others (2021). On education, see Bewersdorff and others (2025), Labadze, Grigolia and Machaidze (2023), Mollick and others (2024), Moundridou, Matzakos and Doukakis (2024), Rudolph and others (2024) and Tan and others (2024). **14.** More rigorously, machine learning excels at eliciting mathematical structure in unstructured data (Dell 2024; Kwon and others 2024). **15.** Baek and others 2021; Jumper and others 2021; Kovalevskiy, Mateos-Garcia and Tunyasuvunakool 2024; Shimanovich and Hartl 2024. This enables advances in many areas of medicine and beyond (Mifsud and others 2024; Topol 2024) and progress towards understanding the cognitive and biology of smell (Smith 2024). For an application of using large language models to elicit political latent positions, see Wu and others (2023).

Expanding science and creativity

The characteristics of AI also create new opportunities for humans to interact with AI in ways that can accelerate discovery and innovation and trigger new frontiers of creativity.[150] Like any other general-purpose technology, such as electricity or the internet, AI will spread in multiple applications across the economy and society, continuing to improve,[151] ideally increasing productivity,[152] a key determinant of standards of living.[153] But AI is, according to economic historian Nicholas Craft, an invention of a method of invention (chapter 6).[154] The US National Academy of Sciences went further in saying that AI is "arguably the most general of all general-purpose technologies."[155] AI can increase the level and potentially the rate of innovation productivity.[156]

> "AI also creates new opportunities for humans to interact with AI in ways that can accelerate discovery and innovation and trigger new frontiers of creativity

Rather than automating tasks in creative processes associated with scientific and technological innovation, the key here is human intelligence augmentation.[157] Automating some nonroutine creative tasks can erode demand for creative occupations.[158] Offloading cognitive effort to AI can reduce critical thinking.[159] AI can increase scientific output but decrease human scientific understanding[160] and variation in scientific outputs.[161] In contrast, leveraging the complementary capabilities of AI and humans to accelerate innovation[162] and creativity more broadly[163] could boost the rate of innovation without these harmful effects. For example, AI models that trained themselves to play chess not only consistently beat humans but also make chess moves that have never been documented as being used by humans before, which in turn inspires top players to improve their performance.[164] Finding ways of bridging the human-AI knowledge gap beyond games could expand creativity across many fields.[165] Creativity involves novelty, surprise and value—even if AI can help with the first two features, value will always be up to us to determine.[166]

Augmenting human intelligence

Beyond the potential to enhance creativity, a key barrier that modern AI can overcome is that nonroutine tasks often rely on tacit or difficult to codify knowledge—largely out of reach of machines in classical programming.[167] What will the increase in the range of tasks and types that can be automated imply for labour demand?

The novel landscape can be intuited by carefully considering the types of nonroutine tasks that are not possible or desirable to automate.[168] For example, some tasks of primary school teachers can be partially automated with generative AI, such as preparing or refining lessons and grading some forms of assignments.[169] Yet others are clearly beyond the practical and normatively acceptable scope of AI, such as implementing discipline or intuiting when students' home lives may require intervention.

The scope of AI's potential for augmentation relates to qualitative changes that intelligence augmentation can yield for human tasks.[170] Three salient but nonexhaustive ways for such augmentation include making advanced expertise more accessible; requiring human evaluation of AI outputs, which creates the need for new types of expertise; and personalizing and customizing rapidly and at scale.

AI makes advanced expertise more accessible

Building on the internet as a repository of knowledge, AI provides a novel means of accessing and recombining that information in a way that can reduce barriers to accessing advanced expertise.[171] Historically, the supply of experts is limited because advanced expertise requires education, training and accumulation of experience through learning-by-doing, which takes time, effort and resources. Although classical programming can often retrieve information produced by experts, consuming this information and applying it to a given task has typically required expertise.[172]

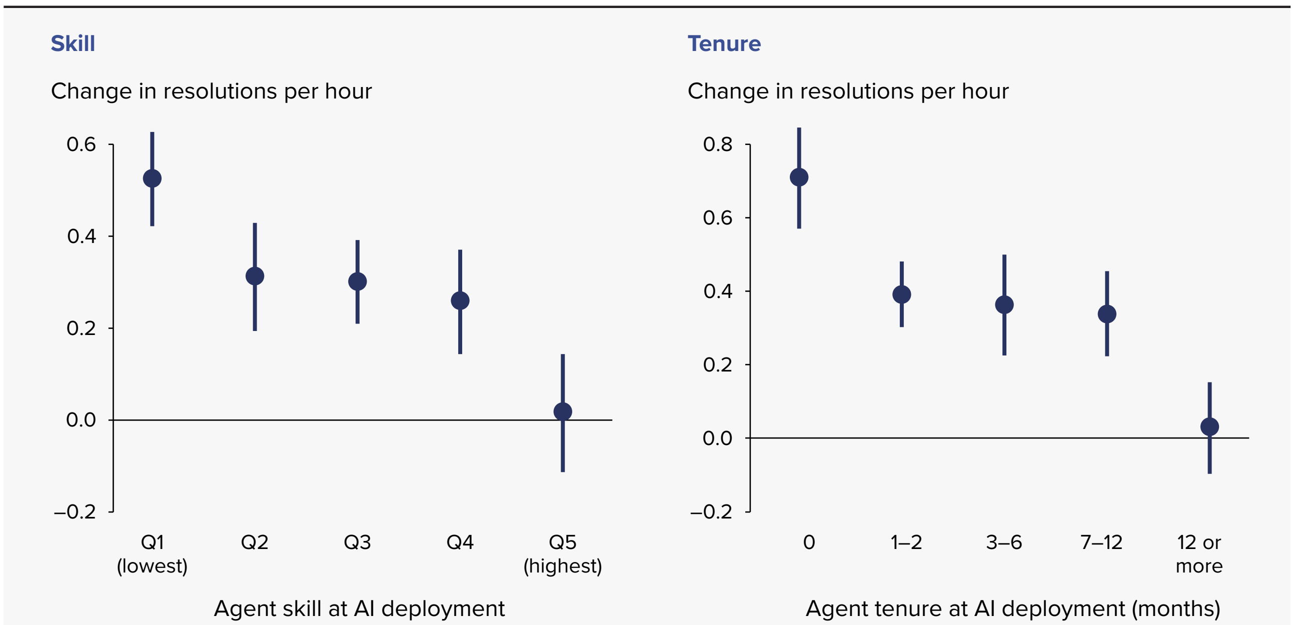
While there is no reason to expect that demand for advanced expertise will decline, constraints on the supply side could be eased given that AI can assist in tasks ranging from computer coding to helping a struggling student understand a math problem to using regular spoken language as a universal interface in healthcare.[173] For example, a recent survey of AI startups found that only 10 percent of their products required users to have expert coding or data skills.[174] A potential implication is that an expanding pool of "functional experts" with advanced expertise could depress the expertise wage premium that emerged during classical programming as a result of the automation of routine tasks. This potential downward wage pressure on high-paying occupations could counter the wage polarization that emerged in many countries, if advanced expertise jobs no longer command outsized premiums—but remain well-paid nonetheless.[175] The US labour market, for instance, appears not to be polarizing anymore.[176]

Reducing the barriers to accessing advanced expertise does not mean that advanced experts do not benefit from AI. For creative tasks higher skilled employees do benefit, consistent with the argument that AI can augment creativity.[177] Early evidence suggests that using AI to accomplish creative tasks reduces the value of domain-specific expertise relative to broader cognitive adaptability.[178] But while AI elevates the performance of professional artists, it also makes the output of laypeople worse by a smaller margin than would have been the case without AI.[179]

However, expanded access to expertise is not wholly without risks. It could result in AI "experts" whose responses merely mimic expertise, ultimately providing none at all and merely justifying whatever answer the requester sought—effectively decoupling aptitude from understanding.[180] Similarly, distillation of some concepts can go only so far or require human subjective judgement, such that decisions based on AI-acquired expertise may be riskier than those from veritable human experts.[181]

Yet tangible benefits of access to expertise through AI already exist. For example, access to AI improves the performance of the least experienced and lower skilled call-centre workers. The benefits decline to undetectable among the most experienced workers (figure 1.8). Similar results have been documented in writing tasks,[182] software development[183] and management consultancy,[184] among others.[185] Younger and less experienced workers appear to be adopting AI at a faster rate, across a range of occupations, potentially enabling them to achieve higher performance more quickly.[186] Those more aware of their own limitations in ability benefit the most from working with AI.[187] These effects may also appear as changes in organizational structures: firms that invest

Figure 1.8 The lower the level of skill and experience, the more workers benefit from artificial intelligence (AI)



Note: Impact on the performance of consumer representative agents after AI is deployed, measured as the change in the number of case resolutions per hour.
Source: Brynjolfsson, Li and Raymond 2025.

more in AI show a flattening hierarchy, with a rise in the share of workers at junior levels and a drop in the share of middle and senior management workers.[188]

Whether these sector-specific findings apply to a broader set of tasks and more complex occupations —and can thus extend to society as a whole—and whether they persist over time remain unknown.[189] If they do, or choices are made such that they do, AI adoption may not polarize the labour market the way the diffusion of classical programming did.

At the same time new gaps may emerge as a result of differences in ability or willingness to use AI, so it is not a given that AI adoption will always have a levelling effect. This is particularly concerning given the evidence of deep gender gaps in the use of generative AI, which persist even when access to AI is enhanced.[190]

AI outputs demanding human evaluation require new types of expertise

Even if advanced expertise is available through AI, some translational expertise may be required to interpret and evaluate AI outputs in many situations.[191] The risk of AI giving bad advice implies, particularly in high-stakes situations, the need for humans to evaluate AI outputs[192] and use AI more as a collaborator than as something that automates tasks in these situations.[193]

> “Taking advantage of AI–human complementarity will probably require new types of tasks and related expertise, in three new roles: explainer, trainer and sustainer

So, taking advantage of AI–human complementarity will probably require new types of tasks and related expertise, in three new roles: explainer, trainer and sustainer.[194] *Explainer* calls for translational expertise, so that outputs from AI can be evaluated and assessed before being incorporated into decision-making.[195] *Trainer* encompasses new tasks such as prompt engineering and augmented generation retrieval to get the most out of AI. It can extend to more upstream tasks of customizing AI models for domain-specific applications—ChatGPT already has hundreds of thousands of user-created domain-specific applications.[196] This is about ensuring that AI works better for intended applications. *Sustainer* encompasses tasks associated with keeping up with AI progress and ensuring that both skills and organizational processes make the most of opportunities as they evolve over time.

AI can personalize and customize services to unique community or individual needs

As the past decade has demonstrated, for better and for worse, AI can personalize and customize services quickly and at scale. Much of the focus so far has been on the ability to personalize messages that can microtarget political and marketing persuasion.[197] But personalization well leveraged can open new opportunities to make bespoke education[198] and healthcare.[199] Indeed, the nonhuman yet personalizable features of AI may similarly allow people facing embarrassing or stigmatizing circumstances to interact with it more easily.[200]

If these personalization possibilities are deployed in ways that substantially improve quality, they could increase productivity in service sectors such as healthcare and education that have lagged the rest of the economy in productivity gains.[201] This may be important in low- and middle-income countries, where employment is expanding more rapidly in services than in other sectors, particularly in settings where the transition through manufacturing jobs is muted or difficult, as discussed earlier. In addition, personalization can also improve the effectiveness of learning and access to healthcare in low-income countries and low-resource settings.[202] Deploying AI to boost personalization of healthcare and education could, over time, increase, rather than depress, demand for healthcare workers and teachers. [203] However, personalization brings new risks, associated with the potential for large-scale profiling, privacy violations and exploitation of vulnerable people, requiring carefully calibrated bounds so that these risks do not outweigh benefits.[204]

Personalization should not be taken so far as to assume AI is a soothsayer able to predict or deterministically alter individual outcomes. AI tools (many of which are machine learning based but not generative AI) that provide predictive information are often sold with the promise of being able to automate decisions, replacing human decisionmaking.[205] In particular, predictive optimization—AI that both predicts future outcomes and makes decisions about individuals based on those predictions (examples include predictions for pretrial risk, child maltreatment, job performance and dropping out of school)—risks systematically failing on its own terms.[206] Recognizing AI's inability to function as an oracle can instead enable it to be a source of informed decisionmaking rather than a substitute.[207]

Envisioning the human development opportunity of AI

Understanding what AI can do, what is new and different from previous digital tools, gives us a way of imagining pathways through which it could advance human development. An important element will be to design and implement adequate policy and regulatory environments adapted to each country's unique characteristics.[208] All countries confront this challenge, but lower HDI countries face the additional challenge that previously available development pathways through export-led manufacturing are narrowing. So how could AI help? Without being exhaustive, here are some possibilities.

"AI does more than offer access to information, which still requires someone to know what to look for through a query on a web search engine. AI can work more as a resource that enables access not only to better information but also to better ways of using that information through interaction with AI and collaboration with other people

First, AI can enable people, organizations and firms to access not only information but also know-how. The internet has provided access to vast amounts of information and new means for global communication, which have created many opportunities and social dividends in low-income settings.[209] But AI does more than offer access to information, which still requires someone to know what to look for through a query on a web search engine. AI can work more as a resource that enables access not only to better information but also to better ways of using that information through interaction with AI and collaboration with other people.[210] AI enables access to something that resembles know-how. It allows for questions that are more open ended and unstructured, in multiple languages and through multiple media (writing, voice) and for responses that organize and interpret information, as well as for suggestions about what else to ask and do.[211] A key constraint in enabling firms in low- and middle-income countries to engage in industrial upgrading (using advanced technologies and products already developed elsewhere) is lack of know-how, which AI could alleviate.[212] Similarly, AI can facilitate the engagement of research institutions in low-income countries with global scientific endeavours.[213]

Second, there are more opportunities to generate positive spillovers from AI investments that spread across the economy. Even when countries succeed in one type of exports to global markets, it is an ongoing challenge to generate employment along the value chain or in other sectors. For example, manufacturing firms in Bangladesh have been successful in exporting garments, generating a lot of employment in that activity, but have had limited success in translating this to activities upstream (design) or downstream (marketing) from garment production or to other sectors.[214] Even the most successful firms in low- and middle-income countries face challenges with established backward and forward links in the country, given that global value chains are, in a sense, premised on those links not being available in the country.[215] And, as shown above, to remain competitive in global value chains, firms in low- and middle-income countries often need to invest more in capital- and technology-intensive production, in contexts where labour supply or high costs are not firm constraints, so gains in firm productivity stay largely within the firm.[216] Investment in AI appears to have greater potential to generate spillovers across sectors, which opens new opportunities for economic diversification (chapter 6).[217]

Third, AI opens new opportunities to expand trade in and increase the productivity of services. On trade AI lowers the language and culture barriers in international communication.[218] On productivity and employment in services, strategies could include:

- Working with large incumbent firms to increase local employment.
- Enabling smaller firms to access and use AI to enhance their productive capabilities.
- Empowering workers directly, in firms or when self-employed, with access to AI in ways that complement low-skilled workers to make them more productive.[219]

More-productive and cheaper services can boost demand when lower service prices allow more people to consume those services, expanding employment further.[220]

Many workers in low- and middle-income countries are self-employed (even outside agriculture) and thus do not benefit from being part of an organization that can specialize tasks, organize the division of labour and invest in technology.[221] For example, two-thirds of the 1 million freight drivers in Brazil are self-employed, but the recent emergence of locally developed digital platforms has enabled productivity increases in this crucial sector by matching workers and freight tasks and improving routing. More than half of road freight in Brazil is intermediated through these homegrown platforms.[222] One tends to think of transport services as being nontradable, but a task-based (rather than product-based) analysis of trade shows that this sector accounts for about 10 percent of exports for countries at all income levels.[223]

> “AI does not require additional physical infrastructure; it is immediately accessible to those online. The drawback is that people who cannot be online face an even bigger disadvantage—even more reason to increase electricity access and close digital divides

Fourth, AI’s flexibility can empower people to seek and iterate solutions to their problems or pursuits that are tailored to diverse and local contexts and even to the unique specificity of individual firms. One challenge of policy advice and development interventions is that they can be overly rigid, as with efforts to promote entrepreneurial activity that do not adapt to different settings or dynamic changes in the economy or society.[224] AI allows for continual experimentation and accumulation of learning over time, further expanding the opportunities already afforded by digital tools for entrepreneurial and small and medium enterprise growth.[225] Small and medium enterprises are often resource-constrained but can deploy AI to identify cost-effective approaches to optimize operations.[226] AI can also be used to improve the supply of goods and services from small and medium enterprises by augmenting the creativity of business owners and employees.[227]

The potential is also vast in agriculture, a sector that still employs substantial shares of people in low- and middle-income countries, many of whom are self-employed and engaged in home rather than market production.[228] AI applications range from making cutting-edge agricultural knowledge more accessible by providing location-specific advice (large language models are sometimes seen to even outperform traditional agricultural extension workers)[229] or more-accurate and real-time weather information (particularly important in rainfed agriculture, as climate change makes this practice ever more challenging).[230]

Fifth, unlike electricity or the internet, access to AI does not require additional physical infrastructure; it is immediately accessible to those online. The drawback is that people who cannot be online face an even bigger disadvantage[231]—even more reason to increase electricity access and close digital divides.[232] In rural areas of low-income countries, electricity has compounding benefits for human development when paired with complementary things people can do with it, so AI can empower these communities in new ways.[233] Equally important are the risks of exclusion from the producer side of AI, which being far from AI-producing hubs and lacking access to computing power can exacerbate.[234] Human capabilities to use AI are also crucial, starting with basic achievements in numeracy and literacy. Only 6 percent of young people in Sub-Saharan Africa, 10 percent in South Asia and 35 percent in Latin America and the Caribbean meet a global standard of basic skills in math and science.[235] But AI can also be deployed to bridge these gaps, with recent evidence showing how AI can be more efficient than the web by helping teachers in Sierra Leone in ways that are 90 percent cheaper than relying on traditional search engines.[236]

There are many potential pathways in which AI can enhance human development, and those outlined above may not pan out. Along with the potential, there are the risks that AI’s deployment will follow the path of classical programming, which was often not pro-worker, given its bias towards automation.[237] Whatever the future holds, development policy needs to be informed by the distinctive nature of AI and what it can do for human development. Envisioning how AI can advance human development can inspire the general direction to aim towards, leaving flexibility to adapt to unique national and local contexts. The remainder of the Report further fleshes out the ways AI can be made to work for people.

SPOTLIGHT 1.1

Humans have agency, algorithms do not

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Is humanity's future still in our own hands? Or will we soon be outcompeted and replaced by machines? Recent developments in artificial intelligence (AI) and the public discussions that surround it can make one doubt. The dominant narrative is that of imminent artificial general intelligence. There is a widespread expectation (or fear) that machines will soon surpass human thinking capacity to achieve some kind of superintelligence.[1] This pursuit of artificial general intelligence goes back to the very roots of AI research. Famously, Alan Turing postulated a test in 1950 (he called it the "imitation game")[2] that would reveal when a machine exhibits intelligence equivalent to that of a human being. However, what this means precisely remains undefined and, on close inspection, undefinable.

Algorithms cannot frame problems

Intelligence, counter to widespread intuition, relies not only on our ability to solve problems (to compute) but also, crucially, on our ability to frame them (to pass judgement on what a relevant problem is in the first place). Evidently, the two are not the same.[3] This is why artificial "intelligence" is such a terrible misnomer: algorithms cannot frame problems. They always operate within a fixed frame. The problems they solve must be defined for them (however flexibly and indirectly) by the human agent who designed the hardware, programmed them, specified their target functions and annotated their training data. It is in this precise sense that algorithms are not intelligent at all! Indeed, as a best-case scenario, the technology we call AI is employed as intelligence augmentation, not to replace us but to increase our own human thinking capabilities.

We may now ask: what is it that enables a human being to be intelligent? What allows us to frame our own problems? And is this something only humans can do? As it turns out, the ability to realize what is relevant for oneself is common and exclusive to all living beings—from a simple bacterium to a sophisticated human being.[4] Obviously, there are huge differences in the degree to which different organisms engage in framing problems and in the complexity of the problems framed. But the fact remains: even the simplest bug can do things that our most sophisticated AI cannot do (and will never be able to) because they lie outside the algorithms' design specifications.

Living organisms manufacture themselves

This special organismic power is called basic agency,[5] and there is nothing mysterious about it. It is entirely compatible with what we know about thermodynamics and the physics of living systems. Agency arises from the peculiar organization of material and energetic flows in a living organism that enable it to manufacture itself. Biologists call this autopoiesis—self-production.[6] No machine that humans have built so far can do this. And it looks unlikely that we will acquire the capability to build any truly autopoietic artefacts anytime soon.

The basic idea behind self-manufacture is a little counterintuitive but not extremely difficult to grasp. The counterintuitive part is that the organization of an organism folds in on itself, like a snake that bites its own tail. It is self-referential or reflexive in a way that our mechanistic machine designs generally are not. In particular, the reflexivity of an organism's organization is different from mere feedback regulation, which we do use a lot in engineering. Feedback occurs between processes that could also exist independent of each other. In contrast, the capacity to self-manufacture implies a living system consisting of physical and chemical processes that not only regulate but also construct each other. Each one could not even exist without the others being present and involved in its own generation while in turn contributing to the generation of other processes. This peculiar way of collective co-construction is called organizational closure.[7] It is the generative principle behind autopoiesis.

In such an organizationally closed system, the causal control over what gets built next lies (at least to some extent) within the circular organization of the system itself. In other words, as a living organism, your future is yours to decide. Within limits, of course: you cannot break the laws of physics, nor should you behave in a way that jeopardizes the integrity of your own organization, as this would mean death. Nonetheless, you have a basic kind of agency because your future actions are (to some degree) autonomous of what is going on in your surroundings. You not only manufacture yourself, but you ultimately also determine the rules of your own behaviour.

Can a piece of software build the hardware it is running on while running on it?

An apt machine analogy would be a piece of software that builds the hardware it is running on while running on it. Or in mathematical terms a model of a whole living organism would have to be based on a system of equations that somehow writes itself. We have very few formal tools today that can help us analyse and understand the behaviour of such self-manufacturing systems.

You may also have noticed the use of "should" above. It means that autopoiesis brings some sort of normativity to an organism's existence: rules according to which it ought to behave to stay alive. These rules are the precursors to our familiar human values: a bacterium "should" go for the sugar and avoid the toxin in order to survive and reproduce. Such norms are not a matter of thoughtful intention in the case of the bacterium but are automatisms shaped through evolution by natural selection. Still, the basic drive to survive, which we presuppose for such rules to exist, is something that comes from within any kind of living system.

And from this drive we also get the idea of relevance: life is precarious, and living beings need to constantly invest physical work into staying alive. This is another aspect that distinguishes them from machines: a chatbot does not get bored between queries because it literally pauses its existence as a computational process when it does not receive or process any input. An organism cannot do that. It needs to constantly work to continue existing—every single moment of its life.

To survive means to preserve your self-manufacturing organization. Accordingly, there are good and bad ways to invest your efforts in survival, some that succeed and some that fail to keep you alive. And with this basic distinction, there come problems that are either relevant or not for you in your particular situation. But if you do not have to invest work into manufacturing yourself, if you cannot perish (because you are not alive and you are not a self), nothing is relevant to you. Algorithms are not alive. Therefore, they cannot solve the problem of relevance, they cannot frame their own problems, because the concept of relevance simply does not exist for them, as they have no self to be manufactured and maintained under precarious circumstances.

Algorithms can only help us grow—and cannot grow beyond what they already are

It should be obvious that this has immediate and profound consequences for policies concerning human development. The basic autonomous agency outlined above opens the path for continued growth and open-ended evolution in the living world. In contrast, an algorithm, operating within its fixed frame, always remains at its characteristic level of complexity. Only autopoietic organisms can transcend themselves.[8] Only they can evolve or learn to exist and behave in more complex ways than they used to, up until now. Algorithms can only help us grow. They cannot grow beyond what they already are. Humans are creative in a way that algorithmic AI can never be.

And this is how, from basic agency, we get the emergence of cognition and thinking in animals with a nervous system and, much later in evolution, consciousness and the whole human experience of intention and reflexive self-awareness. The details of this evolutionary process (and the very nature of many of these higher-level phenomena) are still poorly understood. But it seems highly plausible that autopoiesis, self-production, is a basic prerequisite for all of them.[9]

This should give us a new appreciation of ourselves and everything else that is alive on this planet. Our ability to act autonomously, to be truly creative and to grow beyond our present selves can only be imitated by algorithmic AI technology. This leads us to fundamentally reassess the limitations of AI, as well as other social and cognitive technologies that aim to mimic human thinking and behaviour. For instance, talk of AI agents is grossly misleading. These technologies are sophisticated tools that should enhance our agency and intelligence, but they are not agents in themselves. They cannot replace our creativity, our thinking; they can only supplement it.

Unfortunately, both the prevalent business model for AI and the discussion of its capacities (in particular, claims about artificial general intelligence) are unhelpful in this regard. They misleadingly project (and often actively aim to bring about) a future where it is inevitable that humans will be outcompeted and perhaps even replaced by "superintelligent" technology. Yet, as we have seen, no robust argument supports this view. Machines do not want to take over the world. Algorithms (by their very nature) do not want anything. If machines conquer the world, it is because we, their human creators, have instructed them to do so.

This puts the responsibility straight back into our own courtyard. The buck stops with us. AI by itself may not take agency from us, but humans can employ it in very destructive ways. We can be induced or forced to give away our autonomy, for instance, when algorithms automate creative tasks (AI "art") or decisionmaking processes (including expressing our democratic rights). Applications in surveillance and automated warfare, or the disruption of our social fabric, are also highly problematic aspects of AI—posing potentially existential risks—that should not be underestimated. Yet, truly recognizing the difference between human agency and the lack thereof in algorithmic systems also means that a different future is possible and well within our reach, exactly because we carry our fate in our own hands as autonomous agents.

Algorithms can augment our autonomy, agency and freedom

Instead of voluntarily giving our agency away to algorithms that have a mere semblance of it, we should focus on novel ways of designing and interacting with our technological tools that augment our autonomy, agency and liberty—our ability to take responsibility for our own future—instead of diminishing them. The choice remains ours, and it will become a central concern for human development over the next few decades, as more and more powerful imitatory technologies will emerge and be advertised and sold as "agential" or "intelligent." Under these circumstances it is more important than ever to distinguish hype from reality.

How our complex natural, social and technological context affects us is highly nontrivial. This is not an argument claiming that humans act with unrestricted liberty in isolation. Nor is it an attempt to condemn technology in general. Obviously, there are many positive and powerful uses for intelligence augmentation. In fact, intelligence augmentation is something we urgently need, as our agency gets more and more intricately embedded and extended in an increasingly entangled environment.

But in the end the buck stops with us: the human agents. The source of all this complex agential dynamic ultimately lies within us. It will be crucial for human development in the coming decades that we recognize and remember this simple and empowering fact.

NOTES

1. This term was introduced by philosopher Nick Bostrom (2014).
2. See https://en.wikipedia.org/wiki/Turing_test. The original publication is Turing (1950).
3. Weizenbaum (1976) focuses on this important distinction. See also Dreyfus (1972) or, more recently, Cantwell Smith (2019).
4. For the details of this argument, see Jaeger (2024) and Jaeger and others (2024).
5. Di Paolo and others (2005) provide a detailed and comprehensive definition of basic organismic agency.
6. This is most accessibly explained in Maturana and Varela (1987). For a more technical (but also more rigorous) treatment, see Hofmeyr (2021) and Rosen (1991). On the connection to agency, see Di Paolo and others (2005).
7. Building on the work of Maturana and Varela (1987), this concept was developed by Moreno and Mossio (2015). See also Montévil and Mossio (2015).
8. How organisms come to know the world and how they learn through this experience are described in Jaeger and others (2024) and Roli and others (2022).
9. This argument is outlined in detail in Jaeger and others (2024).

SPOTLIGHT 1.2

A human development perspective on the pursuit of artificial general intelligence

The framework proposed here to provide a human development perspective on the past and future evolution of computational machines is based on the generality of tasks that machines can do, freeing people to do other things and the human effort required for machines to do those tasks. The chapter describes the emergence of pre–Turing machines with the example of the Hollerith tabulation machine. For further context the US Constitution requires a census every 10 years, and with rapid population growth in the late 19th century, the manual processing of handwritten returns, relatively efficient earlier on, took eight years for the 1880 census, for a population of around 50 million. So, in 1890 it was decided to automate key aspects of data processing, specifically the manual tabulation of paper returns, with the Hollerith tabulation machine.

Automating tabulation reduced the processing time to two years for a larger population of 63 million. Yet, the machine did not replace clerks. They still had several other tasks that were not automated (for instance, summarizing data and writing and formatting reports), and the machine created new tasks (such as transferring data from handwritten forms to punch cards that the tabulation machine could read).[1] As with AI and radiologists, the machine to automate a task not only created new tasks for humans but also allowed them to spend more time on tasks that the machine could not do.

Another example is the Colossus computer, built in the mid-1940s and installed at Bletchley Park, England, to help to break encrypted messages during World War II.[2] One of the people involved in this effort was mathematician Alan Turing, who put forward in 1937 a theoretical model of computation that inspired general-purpose hardware able to handle multiple tasks by being fed a set of instructions.[3] The implementation of this idea corresponds to the second stage in the evolution of computational machines, that of Turing machines.

From building hardware to writing software

The human effort to create a Turing machine was not erased but shifted from the physical to the digital. Subsequent generations toiled away at developing and evolving the many technologies in hardware and software required to achieve the performance of today's computers, smartphones and the internet.[4] The torturous pathway from early Turing machines to the modern internet was characterized by punctuated equilibria that time and time again redefined how such tasks were implemented *in silico*. Not until the symbolic encoding of instructions followed by high-level programming languages was the full potential of Turing machines realized to execute tasks with little human effort. Punch cards, a relic of the Hollerith machines, laboriously encoded 80 characters at a time, translating low-level languages to bits and bytes. This process gave way to programs that could be typed out explicitly and a taxonomy of higher-level languages that abstracted away the fine-grained lower-level languages. Each transition was necessary because, just as population growth necessitated the Hollerith machine, the growth in the complexity of software required finding ways to reduce the human effort required to write it.

From letting machines learn on their own to producing machines anyone can talk to

Classical programming approaches faced constraints in executing some tasks that are very easy for humans but very hard to fully specify with a set of instructions, imposing bounds on expanding generality to, say, image recognition. It is easy for a person—and even for a pigeon[5]—to identify a chair in an image, but writing a program that does so is very hard.[6] Just as there were too many citizens to count in the 19th century US, the diversity of objects considered chairs would require an impractically long time to devise a rule set that covers them all. Even if such a program could be constructed, one would likely have to start anew for a program to identify a bed.

Recognizing this challenge, an alternative approach had been pursued since the 1950s: rather than write instructions for the machine to execute, assemble examples of how the task is done and let the machine learn. This marks a third stage: AI implemented through machine learning, which grew in popularity and applications in the 1990s and ultimately proved spectacularly successful at image recognition in the late 2000s.[7] It solved a host of long-standing challenges in image recognition in the decades since, such as detecting suspicious portions of radiological images. Machine learning has extended far beyond images to many other tasks based on predictive models. Advances have been enabled by progress in learning algorithms (particularly using deep neural networks),[8] continuing gains in computer power and massive data availability (made possible with the growth of the internet, the growing digitalization of services and related records, and the emergence of digital platforms).

Perhaps one of the most pervasive and impactful applications of AI in today's world is associated with recommending what digital content to access and interact with—or which products to buy—on digital platforms. AI-based recommendations using recommender systems (chapter 5) are already part of many people's lives. Their diffusion parallels a range of changes for individuals (for example, increases in illbeing for young people) and for society.[9] They are also associated with the potential to trap users into using social media, for fear of missing out, even if many people would rather live in a world without such platforms.[10] Deep learning applications started to emerge as the dominant form of machine learning around 2010,[11] so it is remarkable that this specific application has already transformed people's individual, social and political lives.

The fourth stage in the evolution of computation machines corresponds to generative AI, enabled once again by breakthroughs in algorithms, including the transformer architecture,[12] along with training not on data associated with a specific task but on the vast repository of data in the form of text, images, sound and video on the whole of the internet and beyond. Training has been powered by faster and more powerful computing enabled by graphical processing units.[13]

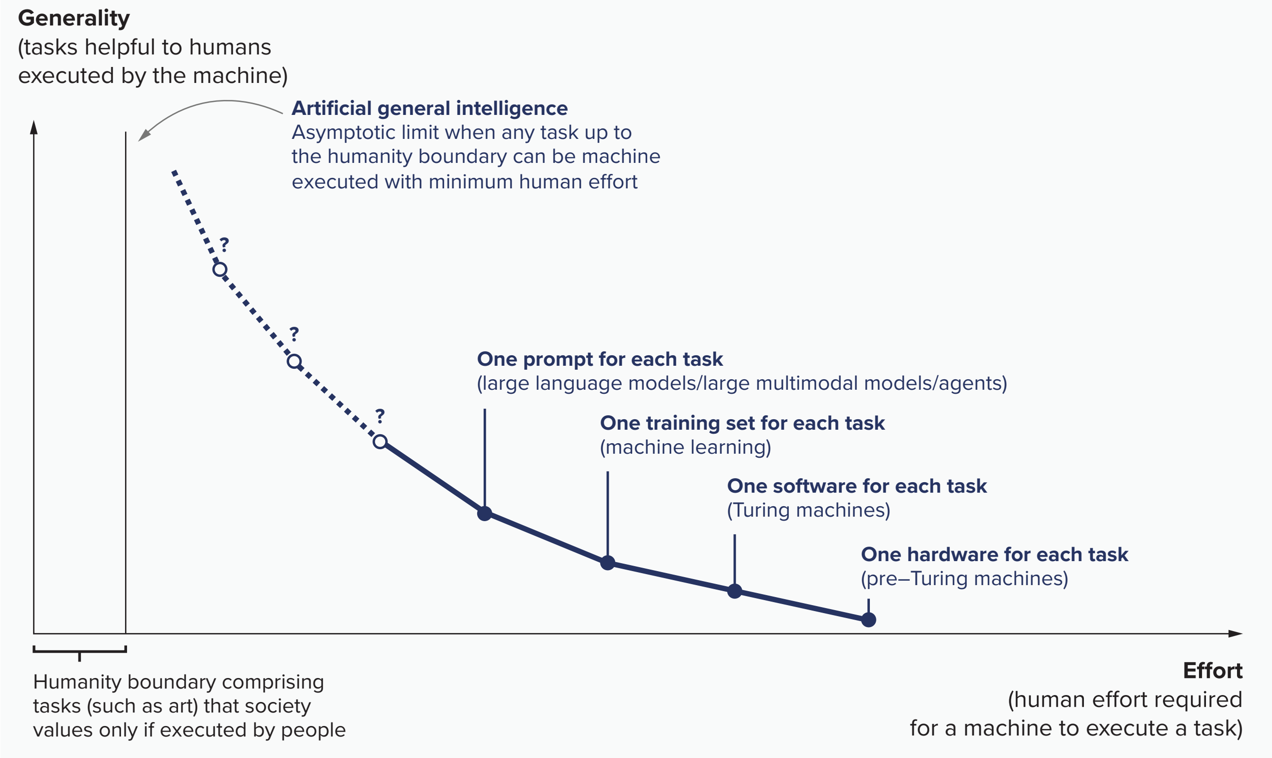
Artificial general intelligence, when we reach it, is up to us, not the technology

We can understand generality on a scale from very low levels (single-purpose hardware of the pre–Turing machines that can perform only one task) to somewhat higher. Correspondingly, the human effort to purpose a machine for executing a task can also be put on a scale. Without formally quantifying these two dimensions, it is possible to illustrate the evolution of computational machines as a progression towards greater generality with lower human effort per machine-delegated task, such that forthcoming stages may be interpreted as the continuation of that evolution.

Generality increases at each stage because it is possible to have the machine execute a wider range of tasks. For example, in classical programming, hardware can be instructed by software to perform different tasks in a prespecified domain but cannot adapt to different domains. That is, we can use a spreadsheet to achieve many numerical tasks, but it would be of little use as a word processor. Current large language models have higher generality because they can handle tasks ranging from writing text to computer coding and beyond.[14] And the human effort required to have machines execute those tasks declines in more-advanced stages, as with computer coding. From the weeks it could take early computers do a different operation, the high-level programming languages increased generality and reduced effort for basic programming tasks with classical programming. And large language models now generate computer code from spoken or written language descriptions in more and more languages.[15] Putting generality and human effort as two axes shows computational machines as a path in which machines can do more things with less effort (figure S1.2.1).

Where do we go from here beyond generative AI? Nobody knows. Experts have different views. Some see the recent models continuing to evolve within the current machine learning paradigm, acquiring ever more capabilities, to the point of posing many risks, potentially existential ones.[16] Others see the current path as inherently limited, an off-ramp that demands new paradigms for progress to continue.[17] Still others think that machine learning is

Figure S1.2.1 A human development interpretation of the evolution of computational machines—more tasks helpful to humans with less effort



Source: Human Development Report Office.

both inherently limited and potentially dangerous.[18] Many are questioning whether the pursuit of human-level intelligence is what should be driving AI research[19]—and even what that would mean is contentious (box S1.2.1).

Although there is no agreed definition of what artificial general intelligence is or even means,[20] there are numerous benchmarks based on different definitions that assess the extent to which progress towards that goal is being made (one example is the Abstract and Reasoning Corpus for Artificial General Intelligence, which also describes several other benchmarks: https://arcprize.org/; another is the so-called humanity last exam: https://agi.safe.ai/). Even what intelligence is or means is contentious.[21] Though there are debates as to whether artificial general intelligence is even possible,[22] the human development interpretation proposed here presents a novel perspective on what the pursuit of artificial general intelligence means.

Artificial general intelligence is interpreted here as a boundary that we can approach indefinitely without ever touching it.[23] That humanity-determined boundary corresponds to the point when any task can be executed by machine with minimum human effort, except tasks that are valued only when executed by humans. The boundary is not fixed and can evolve as processes of individual and public reasoning shape social norms and values. Where could be the boundary be? In one extreme it could be as close to zero as possible—or even at zero. An economy that reaches this singularity is theoretically possible and can be modelled as a coherent economic framework with no (economically valuable) tasks for people to do.[24] But that would be a choice, not something inevitable given the march of technology. In another extreme, society may determine that the pursuit of artificial general intelligence should stop, not because of the fear of the unknown (as with existential risk)[25] but because of an affirmation of a positive act of agency, determining that there are enough tasks done by machines based on an evaluation of the things that people value and have reason to value.

Box S1.2.1 Human intelligence is not defined by that of a single human but of many: Could artificial intelligence get there?

The breadth of tasks for which artificial intelligence (AI) can exceed the performance of even talented individuals is rapidly increasing, resulting in speculation that AI will soon do so at all tasks humans complete.[1] This, in turn, leads to hope and concerns about a forthcoming artificial general intelligence singularity wherein AI surpasses and obviates the need for human intelligence, a key stated goal of several large AI firms.[2] Yet even if a given AI can beat any human at any task, exceeding and replacing human intelligence will remain far beyond the horizon. Although this may seem counterintuitive, the distance arises from the fact that collective human intelligence far exceeds what individuals can accomplish alone.[3] In one famous early 20th century example, individual fairgoers' estimates of the weight of an ox varied widely and tended to be quite poor, yet the average estimate was within 1 percent of the true value.[4] In more applied contexts small groups of radiologists can do far better than even the best individual radiologist.[5] AI performance at this task, and others, will often fall far short of what humans accomplish collectively.

And while it may seem that the solution is simply to create collective artificial general intelligence, science in the intervening century has revealed why this is unlikely to work. Collective intelligence manifests not from large numbers but from complex interactions between the structure of our social networks;[6] our diverse agency and capabilities;[7] our active capacity to inhabit, probe and sense the physical world; and the cumulative accumulation of culture over millennia. Even ostensible human limitations, such as our finite capacity for maintaining social relationships, appear to be features—not bugs—of collective intelligence.[8] By analogy to AI, collective intelligence arises through an evolutionarily adapted network of every human that has ever lived, each possessing a unique and constantly updating training set, prompts and alignment. A single model that exceeds humans on individual tasks, even all of them, is still no match for collective intelligence.

The question then becomes when and how AI can augment human intelligence more broadly. For the reasons outlined in this chapter, replacing humans even with very advanced AI is unlikely to be ideal for promoting collective intelligence. No AI on the horizon will possess humans' capacity to diversely, curiously, continuously and actively explore the physical world and share the information gleaned with others through finely tuned social networks that produce emergent human intelligence. Rather than awaiting such an AI, we can instead rely on existing technology to augment individual humans in their pursuits—leveraging the existing, multibillion-member human superintelligence we already have and depend on.

Notes

1. Narayanan and Kapoor 2024b. **2.** Becker 2024. **3.** Riedl and others 2021; Surowiecki 2005. **4.** Galton 1907. **5.** Wolf and others 2015. **6.** Becker, Brackbill and Centola 2017; Becker, Porter and Centola 2019; Mann 2021. **7.** Navajas and others 2018; Pescetelli, Rutherford and Rahwan 2020. **8.** Henrich 2015.

NOTES

1. Reid-Green 1989.
2. https://www.britannica.com/technology/Colossus-computer
3. Turing 1937.
4. This brief description also glosses over many details (for example, the transition from instructions fed to the computer that were encoded mechanically in punch cards to symbolically encoded computer programs, which was itself a major breakthrough). It ignores the huge human effort that went into the transition from pre–Turing machines to Turing machines. For example, the Electronic Numerical Integrator and Computer, often referred to as one of the first general-purpose computers, was not a Turing machine but was Turing capable in the sense that it was able to execute any computation that could be described by an algorithm (high generality). But it required huge human effort involving physical rewiring for each calculation, with setup times that could extend to weeks (Haigh, Priestley and Rope 2016).
5. Browne 1988.
6. US National Academies of Sciences and Medicine 2024.
7. Deng and others 2009; Russakovsky and others 2015.
8. LeCun, Bengio and Hinton 2015.
9. For a discussion of the broad societal implications of the pervasive use of AI algorithms having power over people's lives, see Lazar (2024a, 2024b, 2024c).
10. Bursztyn and others 2023.
11. Mitchell 2021.
12. Vaswani and others 2017; Yenduri and others 2024.
13. In addition to transformer architecture, other core deep learning generative approaches include generative adversarial networks, variational autoencoders and latent diffusion models (Banh and Strobel 2023).
14. Quantifying greater generality may even become possible given ongoing efforts to quantify the retention performance of large language models when applied to novel tasks that they are not specifically trained for (Maslej and others 2023; Minaee and others 2024a; Zhang and others 2024c; Zhang and others 2025). For example, one metric found that top-performing large language models achieved 50 percent performance on novel tasks (Srivastava and others 2022).
15. Recent evidence has found that pairing computer coders with AI made them code 55 percent faster and that 85 percent felt more confident in their code quality (Gao and Research 2024).
16. Bengio and others 2024; Bengio and others 2025; Cohen and others 2024.
17. Browning and LeCun 2022.
18. Marcus 2024.
19. N. Jones 2025.
20. Mitchell 2024a.
21. Editorial 2024.
22. Fjelland 2020.
23. More formally, this would correspond to an asymptotic limit.
24. Nordhaus 2021.
25. https://futureoflife.org/open-letter/pause-giant-ai-experiments/.

CHAPTER

2

From tools to agents: Rewiring artificial intelligence to promote human development

From tools to agents: Rewiring artificial intelligence to promote human development

To artificial intelligence (AI), decisions are merely tasks to automate. Yet to humans, choice is the currency of agency and the affordance of freedom. As AI becomes integrated into our world, it raises the possibility of automating tedious decisions alongside the specter of inadvertently ceding human agency. The consequences of carelessly ceding agency will be felt not just by individuals in moments but through cumulative consequences for collectives and cultures. Averting loss of human agency to machines requires going beyond a quest for more agentic models and instead favouring development of AI that expands, rather than contracts, human choice, agency and freedoms.

From doing what we do to choosing what we choose

A nearly identical ranking algorithm will just as readily decide the next song on a playlist as it will the next target of an autonomous weapon. Twin decisions and their associated actions, which scarcely belong in the same sentence, are virtually identical from the perspective of artificial intelligence (AI) deputized to automate them. Although it is easy to fixate on the moral distinction between these two contexts, a closer look reveals a shared feature of AI across both contexts—human decisions become mere tasks to automate.

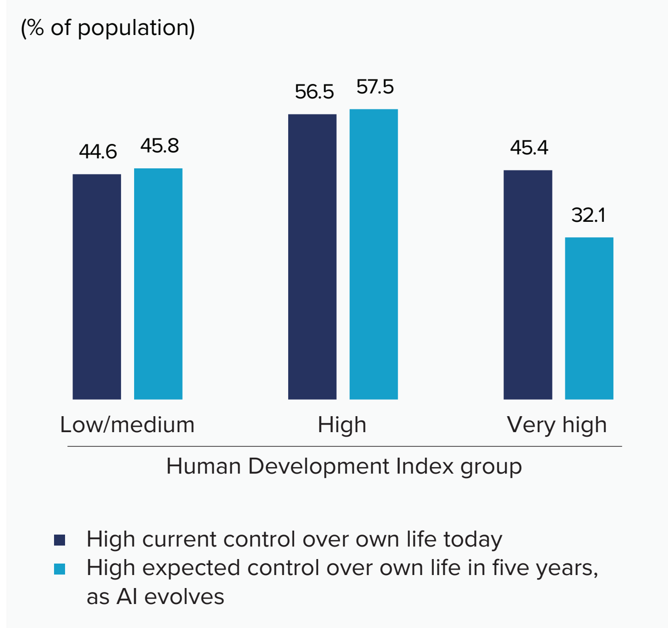
Whereas chapter 1 examines the step-change in how machines have broadened their ability to do what we do, this chapter considers their newfound ability to choose what we choose. Although step-changes in the ease with which novel tasks can be delegated to machines have historical parallels, the same cannot be said for AI's newfound decisionmaking capabilities. From 19th century vote tabulating to classical programming, the construction of the machines themselves has historically been imbued with human decisions. In sharp contrast AI is routinely constructed through machine learning—asking AI to make decisions and providing feedback on those choices. The net result is machines that, by construction, are decisionmaking machines.[1]

This feature of modern machines cannot be ignored because the choices we make express our agency, while the suite of options available to us defines our freedoms.[2] Our agency manifests in why we choose what we choose, something AI cannot possibly know because it can observe only our actions not our preferences. Given this, AI can automate our choices but cannot reliably do so in a way that fully reflects our goals, values, preferences and needs (chapter 5).

In the human development approach expanding freedom and agency is not merely a goal but the principal means through which human development is achieved. When AI restricts the choices we are free to make or reduces our agency to do so, it works directly against human development. But when AI provides a broader swath of more informed choices, it can amplify our freedom and agency. As such, the human development impact of creating machines that can decide for us is difficult to overstate, cannot be neutral and scales multiplicatively with both the newfound abilities of AI and the breadth of its deployment.[3]

This tectonic shift in how digital technologies interact with agency comes at a time when agency itself faces challenges globally. The 2023/2024 Human Development Report noted that nearly half of people worldwide reported not being in control of their own lives.[4] Our survey on AI sentiments echoed those findings and asked participants how they felt about their agency looking forward to an AI-shaped future. The results suggest a gap has emerged, whereby low, medium and high Human Development Index (HDI) countries anticipate few changes in agency, whereas very high HDI countries expect a loss of agency (figure 2.1). Although the causes of this gap remain unclear, one possibility is that increased exposure to AI in very high HDI countries is associated with the sense that the future will be one in which lesser agency is enjoyed.

Figure 2.1 Sense of agency now and in an artificial intelligence (AI)–defined future



Note: Based on pooled data for 21 countries. The sense of agency is proxied by the percentage of respondents reporting high perceived control over their own lives. High current control refers to responses of 8–10 on a 10 point scale to the question "How much freedom of choice and control do you feel you have over the way your life turns out?" High expected control in five years, as AI evolves, refers to responses of 8–10 on a 10 point scale to the question "How much freedom of choice and control do you think you'll have in five years, as digital technologies, including artificial intelligence, become more integrated into daily life?"
Source: Human Development Report Office based on data from the United Nations Development Programme Survey on AI and Human Development.

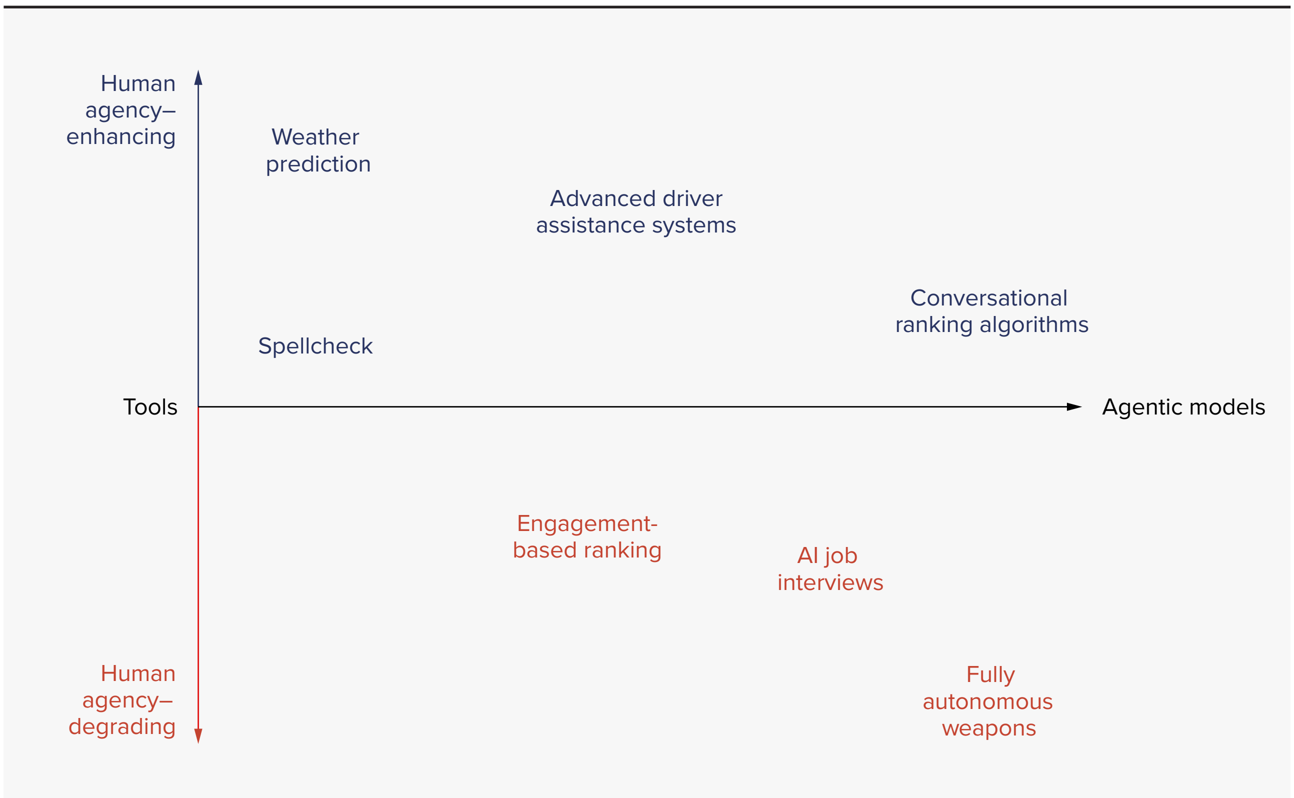
Whether AI erodes agency depends on how it is designed and implemented. Critically, human agency and freedom are not the simple sum of choices we make; nor are they zero-sum in the sense that ceding a choice to AI is losing agency. We may often require decisions to be reached or tasks to be accomplished merely to support more agency-defining choices and actions. For example, few of us can be bothered to pore over raw weather data and decide the probability of rain, but such information may be invaluable in supporting our choices—from bringing an umbrella to raising crops. In delegating such a decision to machines, we expand our own agency in the choices we choose to make.

By the same token none of us wishes for a machine to decide irrevocably in an instant whether we are a combatant or civilian under the Geneva Conventions. The unfreedoms created by a decisionmaking machine quantifying our behaviour to opaquely make such a choice are difficult to overstate. Because we cannot know which actions will tip the balance—carrying a backpack or leaving the house at night—what agency and freedoms could we possibly enjoy? These are not abstract hypotheticals but real-world consequences of deputizing machines to make such consequential decisions.

Herein lies the crux of this chapter: we should not task machines with decisions simply because they now seem capable of making them; we should instead do so based on whether ceding those decisions expands or contracts our agency and freedoms (figure 2.2). In this sense, human development provides a lens for evaluating the use, design, deployment and regulation of AI that enables us to see the value of a system as situated in the real world and beyond its technical capacity. This framing requires letting go of techno-solutionist narratives (chapter 4). In doing so, we may find that existing technologies—not hypothetical future artificial general intelligence—are best suited to improve agency in a given context.

The decisionmaking nature of AI, particularly in combination with its newfound language skills, has

Figure 2.2 Simpler forms of artificial intelligence (AI) may more easily promote human agency, whereas AI with high agenticity can have a broader range of more dramatic impacts



Source: Human Development Report Office.

bestowed on it a remarkable capacity to weave itself into our social fabric. We interact one-on-one with a menagerie of AI, from simple autocorrect and smart thermostats to generative chatbots and digital assistants. AI has also become an intermediary between humans: ranking, sorting, filtering and translating conversations at unfathomable scales. Increasingly, AI is becoming embedded into human institutions as well, shaping their decisions and actions, with cascading consequences for large swaths of the population and beyond the digital divide, as discussed later in the chapter.

“Flows of information through human networks shape the decisions we make collectively, from juries, electorates and governments to globally coordinated efforts to address climate change. Because AI is now a feature of these networks, it will undoubtedly have effects on these emergent decisions

Perhaps the most impactful consequences of AI derive from embedding it in our social systems. So much of human development depends on these human networks, which are often key determinates of our capabilities, functioning, agency and freedoms.[5] Flows of information through these networks shape the decisions we make collectively, from juries, electorates and governments to globally coordinated efforts to address climate change.[6] Because AI is now a feature of these networks, it will undoubtedly have effects on these emergent decisions.[7]

On longer timescales the cumulative product of choices made and remembered defines who we are as groups of people, our culture.[8] Because AI makes—and helps us make—decisions, it will undoubtedly have—and arguably already has had—effects on the trajectories of human culture. Will it be expansive, enabling contextual innovation and broadening our culture? Or contractive, narrowing the breadth of global culture towards a photocopy of the culture that happened to be represented on the internet when training sets were collected? The chapter concludes by highlighting the importance of considering AI's impacts across these larger scales of society and time, as they will invariably shape human development in profound ways.

Against the complexity unravelled in this chapter, it can feel daunting to know where to start and how to move forward. How could we possibly predict, much less intervene on such a large scale, amorphous impacts that may play out over timescales longer than our own lives? Yet the challenge here is, in a sense, no different in scale or complexity than the challenges of human development more broadly. The chapter ends where it starts, arguing that even against such complexity the human development approach can light a path forward—designing, regulating and leveraging AI in ways that scaffold human agency and expand freedoms.

Entering a brave new (digital) world

The human development perspective is anchored in Amartya Sen's view that expanding freedom is both the primary end and the principal means of development.[9] In Sen's view freedom encompasses individuals' capabilities and agency—the options afforded to them and their empowerment to freely leverage those options to pursue goals based on their values and needs. Echoing Sen, the 2001 Human Development Report described technology as a tool for, not just a reward of, growth and development.[10] A quarter century later it is difficult to overstate the internet's impact on shaping and defining the freedoms we enjoy and, by extension, human development. These freedoms are altered not only through direct connection but also through disparity in connection—the digitization of infrastructure, institutions and economies and the spillover effects to other facets of our physical, social and natural worlds.

The internet, having already reshaped human development, recently entered a major transition from a repository of largely passive digital tools to a system replete with a menagerie of artificial intelligences. The pace of this change has been staggering, with technologies that just a few short years ago represented science fiction now being integrated into nearly every corner of the internet and our devices. Data, long a valuable resource, are scraped and hoarded by the petabyte. Massive financial investment has flowed into entirely new markets, promising transformation. The scale of investment into these technologies follows promises that AI will redefine and reshape our economies, education systems, health services and the world more broadly. Even if only a fraction of these promises come to fruition, we should expect large-scale impacts of AI on human development.[11]

But what will these impacts be? There has been no shortage of attempts to predict, manage or gauge AI's impact across domains. Estimates range from a mere bump in the road to global catastrophe—from modest improvements to a brave new world—with most falling somewhere in between. Yet predicting downstream consequences rests on a narrative that technology is something that happens to humanity. It belies the fact that our choices—particularly in the coming years—will determine what those impacts are and, ultimately, what they mean for human development. But this ambiguity indicates plasticity—the freedom to choose what our AI-infused internet looks like before it ossifies. In this sense what AI becomes is not merely a determinant of human development but a manifestation of it.

From tools to agents

The 2001 Human Development Report's emphasis on technology as a tool for development recognized the early internet's promise for expanding agency and capabilities with an ever-evolving suite of digital tools.[12]

Consistent with this, efforts in the intervening decades have emphasized equitable distribution of digital tools through closing the digital divide. See, for example, the increase in the share of the world's population with access to the internet from 16.8 percent in 2001 to 67 percent in 2023.[13] While the proliferation of access to the internet has been remarkable, wide disparities remain in quality, reliability and means of connecting.[14] Moreover, the capabilities that connecting to the internet provide vary widely and are linked to the key components of the HDI: income and achievements in education and in health. Connecting to the internet remains an important development priority because it can enable individuals to access and contribute to the global knowledge commons and participate in the ever-growing digital economy.

The tool-like quality of early digital technologies undergirded their promise as a force for development. Many tools on the early internet were simply more equitably distributable or more efficient versions of tools in the physical world—for example, email, online banking, calendars and digital encyclopaedias. From the human development perspective tools in the digital world resemble tools in the physical one (table 2.1). Tools have well-defined purposes that can be understood and taught. Human action predictably links to outcomes, and this relationship remains stable over time unless the tool's design is intentionally changed. Perhaps most important from the human development perspective, tools do not choose things for us—keeping human agency front and centre.

As chapter 1 discusses, AI represents the latest step-change in our ability to create machines capable of accomplishing ever more general tasks. Particularly when developed through machine learning, AI is implicitly decisionmaking machines—even when the decisions are as trivial as spellchecking. In this sense the simplest forms of AI bear much resemblance, from the user's perspective, to tools. The decisions they make are inconsequential or predictable enough to simply save us time (spellchecking, smart thermostats), or they reliably make accurate decisions we could not make (weather prediction, translation).

Yet more advanced forms of machine learning converse, generate videos, play games and identify candidate drugs (box 2.1). This general breadth of task completion comes alongside expanded decisionmaking. In this sense the capabilities and nature of these systems bear little resemblance to tools. A tool provides an individual with well-defined affordances that they can learn to use, resulting

Table 2.1 Comparing characteristics of digital tools and artificial intelligence (AI) agents

Feature	Digital tools	AI agents
Predictability	Consistent and predictable	Often unpredictable
Transparency	Easy to understand and explain	Opaque, difficult to interpret
Behaviour	Static, unchanged unless updated	Dynamic, evolves over time
Role	Passive, user-driven	Active, can act autonomously

Note: These are not absolutes but ends of a spectrum. A given implementation of AI may behave more like a tool in one or more ways, but AI is unique in its ability to exist along these continua.
Source: Human Development Report Office.

Box 2.1 Artificial intelligence revolutionizing biomedicine

Generative artificial intelligence (AI) has the potential to generate much more than text, images and video, and there is substantial interest in applying AI to biomedical research and development. Two active intertwined areas of research surround protein folding and drug discovery. Proteins are large molecules synthesized within cells from amino acids that serve various functions and are common targets of medicines intended to treat disease. Discerning their three-dimensional shape is essential for understanding their function and developing drugs that target specific proteins. More recently, mRNA vaccines have made it possible to encourage cells to generate proteins not found in their genetic code, with promising applications for allergies, infectious diseases, cancer and genetic disorders.

Unfortunately, computing the structure of a given protein has historically been computationally intensive, requiring access to larger servers or distributed computing efforts such as Folding@home.[1] Recent advances in AI, such as AlphaFold3, can predict the structure of proteins at drastically reduced computational cost with increasingly high accuracy.[2] Challenges of protein folding are intrinsically linked to AI-powered drug discovery, which seeks to identify compounds that often interact with proteins, such as receptors or enzymes, to produce some desired biological effect. Ideally, the compounds already exist and are approved for treating other conditions.

AI applications for drug development are on the rise because they can rapidly propose and assess candidate drugs, potentially speeding discovery and aiding in identifying promising candidates. AI can be further used to develop pathways for drug synthesis or to speed up testing of proposed drugs. Investment in AI-fuelled drug discovery is ramping up, with the first AI-discovered drugs hitting the market in 2024.[3] Although the use of AI in medicine is nascent, there is little doubt that it has big potential to advance the field in the coming years.

Key challenges remain in making these technologies more widely accessible so that research and development can be expanded beyond a finite set of for-profit institutions and well-funded universities. One such effort, ColabFold, was developed in 2022.[4] This free and accessible protein folding platform provides better functionality than Google's last-generation AlphaFold2, making it a viable option for some protein folding tasks. Investment in open-source AI models for biomedical research may be critical for expanding biomedical research and development leveraging these tools.

Notes

1. Larson and others 2009; Voelz, Pande and Bowman 2023. **2.** Abramson and others 2024. **3.** Ren and others 2024. **4.** Mirdita and others 2022.

in a specific expansion of capabilities—importantly, it makes no choices for us. By contrast, an AI-based system may behave differently across users and contexts, in essence adapting its behaviour to context. This challenge is particularly salient in personalized recommender systems, where two individuals in different locations who conduct the same web search receive very different results.[15]

This dynamic feature of AI-powered systems can be valuable. For example, it can provide locally tailored information and avoid irrelevant information dominating search results. In this sense the choice to return only locally relevant results is one we might reliably make ourselves—such as choosing to examine results only in a language we speak. However, personalization can also have varied impacts on the quality of items surfaced across platforms, from surfacing less-divisive, higher quality information to the opposite: amplifying misleading, ideologically aligned content.[16] Here, the choice is more consequential—to what extent would we choose to spend time reading low-quality information, given the choice? Would we choose to have our views reinforced by such low-quality information or prefer to engage with something closer to the truth? These decisions may be silently made for us in an instant, beyond our view.

This unpredictable nature of AI raises a host of additional development challenges at scale, as the same system may result in very different outcomes across individuals, contexts and time. The differing outcomes may, in turn, exacerbate existing inequalities. For example, some users may receive higher quality information from the same search product merely because of their geographic location or other aspects. In this sense deprivations of agency-impactful choices may not be uniform.

Similarly, the function of more straightforward digital tools can be inferred by evaluating the underlying code. One could browse the code powering a simple email service and deduce that it enables individuals to send one another messages. This functionality can be taught to users, promoting agency when deciding whether and how to use email. Reading the code underlying generative AI, one could infer that it learns something from some data and produces responses. Yet there is no way to trivially evaluate the trillions of potential parameters and petabytes of data that define what it learned and how it might respond. The resultant opacity makes it difficult to know why more complex AI systems choose what they choose and whether their choices reflect the choices we would make. Indeed, it may even be hard to know which intermediate choices they made before arriving at a result or decision.

> “The resultant opacity makes it difficult to know why more complex AI systems choose what they choose and whether their choices reflect the choices we would make

Many AI systems are not simply trained once but are instead refined with data and experience.[17] As a result, even if the behaviour is well-characterized, it may change over time, perhaps suddenly and silently, rendering our understanding of impacts and any implemented interventions obsolete.[18] Moreover, the development of AI is progressing at a speed far outpacing what can be expected for scientific and regulatory responses, frustrating typical approaches to identifying and mitigating harm. This dynamic nature of systems makes AI technologies a moving target such that any development-minded applications will require continuous reappraisal as the systems evolve and alter their behaviour. From an individual's perspective, even if they are comfortable delegating choices to a machine at a particular moment in time, they may have no way of knowing whether and when that machine begins making different choices that no longer reflect their agency.

This decisionmaking capacity is made even more salient when AI can act on its choices. Some AI systems are, like tools, passive and require human input to produce output or have meaningful impacts. Software that judges use to predict recidivism requires inputting characteristics of the person being evaluated for release.[19] While it can make recommendations, judges ultimately bear responsibility for any decisions. Autonomy here is defined not by the tool itself but by the degree to which (if any) judges' decisions are constrained by law, norm or convenience to follow the algorithmic recommendations. In other cases AI systems will be explicitly designed to initiate actions or make decisions (semi-)autonomously in response to changes or incoming information. Automated trading systems, for example, can move money in response to market changes, exerting substantial force on financial markets, with minimal, if any, human oversight.[20] Automation raises challenges when choices have meaningful consequences, because the impacts of decisions can accumulate without human oversight—fully divorced from human agency.

Making AI explain itself

The unpredictability of AI agents has been a critical challenge to their deployment in real-world contexts. AI agents can behave dynamically, actively and autonomously, leading to the alignment problem, identified more than half a century ago by computer scientist Norbert Wiener.[21] The behaviour of an AI system is often shaped implicitly through learning specific tasks in a controlled environment. On deployment the system may be used for a much wider variety of tasks across a broader range of outcomes, leading to unpredictable behaviour.

Yet the predictability, explainability and general dynamism of an AI system are not discrete states—they represent continua along which a given implementation of AI sits and can be adjusted. Anticipating risks, promoting human agency and ensuring accountability can be facilitated by intentionally designing AI so that humans can inspect and understand how they work.[22] Often referred to as explainable AI or explainable machine learning, these systems promote human intellectual oversight of AI by ensuring that humans can understand why inputs to a given AI system result in a specific output.

Not all applications and approaches to AI are amenable to explainability. For those that are not, AI audits hold promise for characterizing how an AI system functions, its risks, biases and other relevant factors (chapter 5).[23] Audits may reveal the need for refinement and reshaping before deployment.

Shaping alignment can take various forms, often involving further AI training through feedback from other AI, through explicit heuristics and constraints or through "humans-in-the-loop."[24] Each of these methods is an imperfect iterative process that may require continual and ongoing shaping as the behaviour of AI, its uses, its users or the context in which it is deployed change. In some cases it may be necessary to restrict AI technologies that cannot reasonably or sufficiently align with human wellbeing.

AI's ability to do and choose does not give it agency

Were it just for the unpredictability of AI systems, efforts to rein in and characterize AI behaviour could be sufficient for making systems tool-like. Yet the unique decisionmaking and action-taking capabilities of some AI systems fundamentally change the calculus of AI from a human development perspective. The degree to which AI systems can autonomously accomplish a range of more general tasks is often referred to as agenticity—a nod to their capacity to act as agents. AI systems with low agenticity may narrowly serve simple functions with heavy human oversight (see figure 2.2). More complex forms of AI, such as modern chatbots, can be repurposed for a wide range of tasks they can undertake with whatever degree of autonomy is afforded to them. The race to build more and more capable models is implicitly a race to develop more agentic forms of AI.

Techno-solutionist narratives, explored in chapter 4, often suggest that simply building more agentic models can solve the world's problems. Yet the human development lens provides a starkly contrasting view. Because our own human agency is expressed through actions and decisions, AI's agentic capabilities hold promise to expand our ability to make and act on choices, alongside a very real risk of ceding human agency to technological artifacts. Developments in the past two years have drastically increased the agenticity of AI, commensurately broadening the ways it intersects with human agency (see figure 2.2). Whether this increased agenticity improves or degrades human agency depends on the choices we make in the coming years.

> "Whether highly agentic systems ultimately promote or degrade human development depends not on their technological capabilities but on the way they are integrated into society—a theme explored throughout this Report

There is no trivial or zero-sum relationship between the agenticity of AI and its impacts on human development. AI systems with low agenticity can, and routinely do, dramatically improve human agency. Weather prediction, for example, is far from autonomously able to take broad-ranging action—but can provide individuals with essential information to support agency. These systems provide critical information for making decisions as mundane as bringing an umbrella and as consequential as crop management, city planning and emergency evacuation. Weather prediction systems could be made more agentic, sending automated tailored messages and answering questions in regular spoken language, automatically translating as needed. Provided these systems are trusted and accurate, their anticipated consequences for human agency would be net positive.

Yet the same underlying generative language model leveraged to support disaster communication could be purposed to create deceptive bots or write misleading news articles that persuade individuals to make decisions against their interests and values. Even more consequential uses of highly agentic systems have begun to occur on battlefields. Some examples of AI demonstrate how highly agentic models convey both greater opportunities and greater risks for human development (see figure 2.2). Whether these highly agentic systems ultimately promote or degrade human development depends not on their technological capabilities but on the way they are integrated into society—a theme explored throughout this Report.

Given the centrality of agency in the human development framing, it is important to remain aware of distinctions between human agency and machine agenticity. There is no reason to believe that because AI can make and act on decisions, it does so using similar (or any) cognitive processes to those of humans.[25] Nor does framing AI as agents or agentic imply that we should strive for machines with humanlike agency. Instead, we must anchor our choices for developing and deploying AI in ways that expand human agency and capabilities. These technologies must be designed so that whatever decisionmaking we cede to AI complements and expands rather than contracts freedom. AI technologies should be viewed not as tools of human development but as agents whose behaviour, alignment, training and use can profoundly impact human development and security. Ultimately, agenticity is not a goal but a design choice to be made solely when it supports human agency (chapter 5).

Approaches to ensuring AI accountability and reducing uncertainty are rapidly evolving and will doubtless continue to do so, given the rapid pace of change in AI functionality and deployment.[26] At present, there is minimal accounting of the harms caused by AI and, similarly, minimal visibility on how it is being deployed and used.

Embedding AI into our social fabric

Online connections between humans

The printing press, radio and television increased the flow of information between humans, but the internet has been distinct in reducing the costs of producing and distributing information.[27] Analogue technologies tended to consolidate the production and distribution of information in the hands of those with the infrastructure for distribution. These few-to-many communication systems—often still geographically constrained—fundamentally differ from the global all-to-all systems afforded by internet connectivity.

Connections between humans are in many ways the primary source of both opportunities and challenges to improve human development. The 2023/2024 Human Development Report evaluated some critical barriers to successful human collaboration, the rise of gridlock and what can be done to prevent it.[28] Historically, the successes, failures, inequalities and many development challenges have emerged directly or indirectly from the dynamics of interactions between humans.[29] Ultimately, the challenge of guiding our world towards one that is sustainable, equitable and healthy is a challenge of understanding how to promote successful interaction between humans.[30]

At more minor scales than global decisionmaking, it is difficult to overstate the importance and benefits of communication between humans. Social interactions facilitate social mobility, promote mental and physical health, increase longevity and are essential to a good life.[31] More generally, our social institutions and interactions shape our skills, inform our decisions and alter our opportunities—crucial determinants of human development.[32] Much of the development potential of the internet lies in its capacity to augment interactions between humans, reducing geographical, infrastructural and systemic barriers to communicating while increasing the ability to share and access information.

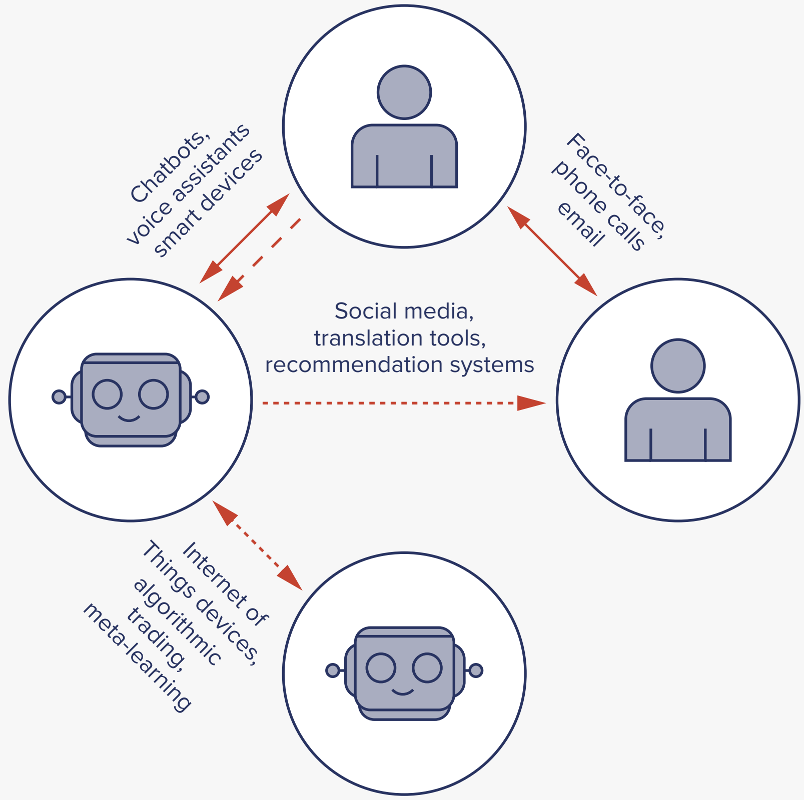
> “By inviting machines into our social networks, the choices they make begin to impact us through our social networks in much the same ways that we impact one another

The proliferation of AI in the digital spaces we increasingly inhabit presents a qualitative shift in how we interact with one another and the physical world. As outlined below, social networks now comprise direct interactions between humans and AI, AI-mediated interactions between humans and an increasing but largely unappreciated impact of interactions between AI systems (figure 2.3). This in turn shapes the choices we can and do make, as individuals and as groups. Moreover, by inviting machines into our social networks, the choices they make begin to impact us through our social networks in much the same ways that we impact one another. The following sections evaluate how integrating our social systems with decisionmaking machines can profoundly influence choices and their consequences, from the scale of individuals in day-to-day life through societal processes that take place over generations.

Interactions between humans and AI

Regardless of whether we notice, we increasingly interact with, and cede choices to, various forms of AI. AI in some form is required to filter, sort and display the vast amount of information on the internet in a form that our finite attention can process (chapter 5). In more conspicuous cases we find ourselves conversing with automated systems in customer service agents, digital assistants and multipurpose chatbots. Leveraging these explicit cases of interaction between

Figure 2.3 **Interactions between and among humans and artificial intelligence**



Source: Human Development Report Office based on Brinkmann and others (2023).

humans and AI is an area of considerable ongoing research and development across domains. In medicine accurate diagnoses are essential to effective treatment, and diagnostic accuracy directly affects human development. Numerous AI systems are being developed daily to improve diagnostic capabilities. For instance, endoscopists codiagnosing alongside AI resulted in higher diagnostic performance than either AI or humans acting alone.[33] Other applications of explicit interaction between humans and AI are being developed in contexts as varied as addressing erroneous beliefs; getting information about government services; providing financial, legal and medical advice; counselling; and developing software.[34]

Sometimes, human–AI interaction can be more subtle, augmenting capabilities in ways that feel much more like using a tool than holding a conversation. For example, advanced driver assistance systems in vehicles encompass a range of technologies that leverage the high sensitivity of digital sensors to warn drivers of hazards, detect and offset fatigue and initiate action such as braking to avoid collision.[35] These systems could reduce common types of traffic accidents by 16–40 percent.[36] With more than a million traffic deaths a year globally, reductions in accidents from expanded access to advanced driver assistance systems could directly improve life expectancy and, by extension, human development.[37] Because traffic deaths are considerably more prevalent in low HDI countries, improving access to these systems could be particularly promising.[38] But cultural differences in moral appraisal of advanced driver assistance systems may require adapting them to local norms and values.[39]

Interactions between humans and AI can also facilitate learning for both. For example, AI-powered identification of bird species can enable users to better identify them in the future.[40] The increased ability to identify species can, in turn, improve AI's performance by directly contributing geolocated observations and uploading labelled sounds and images. This recursive process and the data it generates have become an essential tool for conservation.[41]

Well-designed AI can thus leverage humans' unique capabilities to explore the world and augment them with the effortless ways computers can store and process information. And such systems can be aligned to benefit individuals and broader development goals. These examples are just a handful of the many ways AI can enhance individual capabilities, a theme throughout the Report in contexts such as education, healthcare and employment.

Now consider the pitfalls. Many of the freedoms and capabilities the internet provides depend on expanding access to high-quality information. One of the more common ways humans engage with AI is through various recommender systems that sort and filter news, information and entertainment across the web. Often aligned for engagement and advertising sales, these systems can narrow information diversity, heighten confirmation bias, promote addictive behaviours and lead individuals down "rabbit holes" and into harmful behaviour (chapters 3 and 5).[42] The same image recognition technology enabling visual forms of search powers facial recognition software used to restrict freedoms and harass.[43] Ultimately, the extent to which such systems exhibit these freedom- and capability-limiting effects depends inherently on whether they are designed in a way that keeps human agency and freedoms front and centre.

AI-mediated human interaction

AI intermediaries increasingly facilitate or alter interactions between humans. In simple cases AI can convert information generated by one human into a format that another can more easily receive. For example, different languages have long been a barrier to interaction between humans. The languages one can speak or read can profoundly affect access to information, economic opportunities, quality medical care, education and government services. Effective machine translation has long been a goal of AI research, and recent models have a remarkable ability to cheaply and quickly translate across hundreds of languages.[44] But these models are far from perfect and can produce false translations (hallucinations) or toxic language.[45] Even so, given the cost and shortage of human translators, they hold remarkable potential to bridge language divides. Within a given language AI has been leveraged to smooth otherwise polarizing conversations—helping establish common ground.[46]

"AI's ability to process natural language opens the possibility of accessing and generating digital information even if one cannot read or write. This potential to broaden accessibility is particularly relevant to development, as it can help in overcoming barriers to accessing the benefits of our digital world for those previously limited by design that makes implicit assumptions about their abilities, literacy and language fluencies

Beyond language AI can be used in various ways to smooth communication between humans. Information shared in one format, such as text and images, can be converted to audio and descriptions of images for consumption by someone else. Similarly, AI's ability to process natural language opens the possibility of accessing and generating digital information even if one cannot read or write. This potential to broaden accessibility is particularly relevant to development, as it can help in overcoming barriers to accessing the benefits of our digital world for those previously limited by design that makes implicit assumptions about their abilities, literacy and language fluencies.

When AI facilitates conversation between two individuals, it may be clear there is an AI intermediary—or it may not be. The impact of AI may be subtle or unknown to users. For example, much of what we encounter online may be created by humans but ultimately curated and ranked by machine learning. Given the vast amount of information online, some form of curation is inevitable, and AI condenses large volumes of information into a form that is readable by humans. Whether and how these AI-mediated interactions expand or contract capabilities and freedoms depend on how they are designed and implemented.

Consider interactions between humans on social media platforms, mediated by machine learning algorithms that rank, sort and filter what users see amid the content others post. Such algorithms are aligned primarily with increasing firm revenue through a business model that translates engagement into ad sales and revenue.[47] So, how human interactions are mediated is not aligned with promoting human development (chapter 5). Humans can in turn alter their behaviour in response to algorithmic feedback—for example, leveraging language that provokes engaging emotional responses.[48] Thus, algorithms not only shape what interactions occur between individuals but can fundamentally alter individual behaviour in social contexts.

> "That the same AI mediation between humans can lead to vastly different outcomes across contexts highlights how the effects of a given system cannot be viewed in isolation. Likewise, attempts to intervene and improve the alignment of algorithms will need to consider not only harms but also the potential loss of benefits

Balanced against these potentially detrimental impacts, AI-mediated online interactions between humans can improve job opportunities and engagement in democratic processes.[49] These positive outcomes are well-aligned with human development yet emerge from the same platforms and algorithms. That the same AI mediation between humans can lead to vastly different outcomes across contexts highlights how the effects of a given system cannot be viewed in isolation. Likewise, attempts to intervene and improve the alignment of algorithms will need to consider not only harms but also the potential loss of benefits.

Beyond social media AI has become an important intermediary between humans in contexts extending beyond the digital world. Judges, employers, banks, landlords and schools use AI tools to evaluate individuals' suitability for release, employment, lending and housing.[50] Across industries large datasets determine prices for goods and services, at times dynamically in response to fluctuating demand or even tailoring prices for individuals and markets.[51] In the academy AI is cropping up in the production and review of manuscripts—despite experts' calls for caution—embedding itself into a core mechanism through which society gathers and consolidates its understanding of the world.[52] AI similarly mediates cultural markets, differentially favouring some content producers over others.[53]

Interactions between AI agents

AI systems routinely interact with one another. Given the remarkable speed at which computers can process and transmit information, these interactions can happen with an incredible degree of speed and scale. They can be direct, mediated by a human or indirect because of interactions in the same common space (such as a market). The dynamics of these interactions may be more challenging to observe, and their impacts on human development are difficult to predict and identify directly and in a timely manner.

A classic example is automated financial trading, where AI agents either autonomously or semiautonomously trade financial instruments in response to market fluctuations or other information. This approach to trading is remarkably commonplace, as machine learning can outcompete humans in many relevant contexts, particularly on short timescales. Such interactions can reduce trading costs and improve financial inclusion for everyday investors but also increase market uncertainty.[54]

In algorithmic trading AI agents have similar goals, yet very distinct AI systems can interact in the same way. For example, machine learning predicts and collects characteristics of individuals on Facebook for targeted advertising. Advertising companies may leverage AI to best use targeted advertising such that an AI system is operating on data compiled by AI to place ads in a system that targets based on AI. Laws intended to protect individuals can be violated without a human in the loop. In one case Facebook's advertising platform enabled unlawful discriminatory housing advertising.[55]

Interactions between AI systems can also improve those systems' capacity and adjust their behaviour and alignment. Although machine learning often involves training agents on data, interactions between AI systems can enable training for some tasks, even when data are scarce. Google's AlphaZero, trained to play chess solely through self-play, consistently beat other chess engines.[56] Its successor, MuZero, was developed to learn arbitrary games through self-play, making for a much more general architecture. Beyond games these approaches could help develop AI in rule-based contexts without the need for massive volumes of data.[57]

Similar approaches are emerging for relying on AI to guide the behaviour of other AI systems. For example, one large language model can annotate output features from another to provide feedback for further training and refinement.[58] These types of mutual learning can be used in isolation or augment training involving human annotation and guidance. These are just a handful of examples highlighting how autonomous agents can interact with one another. Such interactions can be viewed as amplifiers that increase AI systems' abilities and complexity, which may make behaviour opaque and more unpredictable. Compared with interactions between humans and AI, however, these interactions are feasible to simulate and evaluate *in silico*. Research on interactions between AI systems in the wild is limited, and understanding the impacts and potential for human development will be crucial in the coming decades.

AI and institutions

Human agency is often expressed and affected by decisions at larger scales of organizational complexity—institutions. Indeed, the early uses of AI in the 1990s were for business and military decisionmaking.[59] When institutions rely on AI, they cede some agency in information aggregation or decisionmaking to AI. Decisions once under the purview of consultants, war rooms and board rooms are shaped or even made *in silico*.

"The use of AI in institutions has unique considerations when viewed through the lens of human development. The concerns and opportunities may shift from those working directly with AI towards how its use alters the institutional impact on human development

The use of AI in institutions has unique considerations when viewed through the lens of human development. The concerns and opportunities may shift from those working directly with AI towards how its use alters the institutional impact on human development. Depending on the scale and nature of the institution, AI-coupled decisionmaking in and between institutions may have outsized impacts on human development. Perhaps the most salient way AI can shape institutional decisionmaking is by parsing and aggregating large amounts of data. This transition to big data and machine learning has been under way for over a decade, with large datasets and machine learning now the norm for many institutions rather than the exception.

Often, the benefits of such applications are front and centre, motivating the use of a given technology in the first place. Machine learning can help institutions better allocate and target resources, increase the efficiency of internal processes and provide relevant information beyond the scale of what can feasibly be discerned from raw data alone. For example, the government of Togo leveraged AI to identify individuals most likely to benefit from financial assistance during the Covid-19 pandemic.[60]

However, AI that does not—or that cannot—accomplish its stated goals poses a real risk of, at best, waste and, at worst, causing harm or degrading decisionmaking.[61] For example, software for predictive policing did little more than send police to the same areas where they historically made arrests, exacerbating biases and failing to actually "predict" anything useful.[62] More generally, institutions hoping to leverage AI would do well to invest in audits and to ensure that those audits are effective.[63] Whether AI can accomplish a task assigned to it—when its use in an institution improves or degrades human agency and freedoms—depends on the alignment of the institution itself. If AI is leveraged to degrade human rights, coerce consumers or replace good jobs, it may be at odds with human development.

The examples here cover common and established uses of AI. Given the rapid change in the AI landscape, there has been equally fast adoption of opaque, less-explainable models in institutional systems. This may be intentional, such as relying on AI to synthesize reports in service of decisionmaking, or surreptitious, AI-written text, perhaps with hallucinated facts creeping into the decisionmaking process. As a first-order priority, institutions would do well to develop policies governing the use of AI and processes for delineating human- and AI-produced information and temper excitement about new technology with careful and considered application.

AI, humans and the physical world

The rapid growth in AI's capabilities, development and deployment results in a similarly dramatic increase in how AI directly and indirectly learns from, interacts with and affects the physical world. AI can be fed information from any internet-coupled sensors to collect and respond to real-time data on traffic, weather, stock markets, wildlife or other domains. Such information can inform human decisionmaking or directly and autonomously result in actions affecting the world. And AI systems can be embodied in robotic systems that enable them to interact with the physical world and accomplish tasks directly.

> “As with all digital technologies, AI is not without its direct impacts on the environment, climate and sustainability

AI's potential to buffer humanity in the Anthropocene offers promise and risks. AI is already helping detect sources of emissions, improve agricultural efficiency, aid conservation efforts, improve weather prediction, promote renewable power production and facilitate sustainability more generally.[64] But it has also been applied to increase fossil fuel and cattle production—risking AI-increased rates of carbon emissions.[65] As with all digital technologies, AI is not without its direct impacts on the environment, climate and sustainability.[66] Models can be resource-intensive to develop and train. The information technology infrastructure that supports AI comes with its footprint in the natural world, not just in terms of energy but also in the extraction of finite resources, water and rare materials.[67] When well-aligned with sustainable development, these indirect benefits would ideally offset direct impacts.[68] But there are few guarantees that this will occur without active policy steps to reign in the ecological consequences of AI and harness its potential benefits. Indeed, AI seems to have reversed or stalled some companies' pledges to reduce their environmental impacts.[69]

Beyond the natural world, AI is being readily integrated into our infrastructure and civil services. As described earlier, advanced driver assistance systems in vehicles are becoming more commonplace, and AI-powered navigation systems offer emissions-efficient routes. The move towards smart cities leverages AI to make sense of massive data from sensors and to inform policy—creating privacy concerns.[70] AI streamlines supply chains and powers more complex robots in factories and warehouses.[71] Governments are evaluating and deploying AI to help distribute key services to citizens.[72] Machine learning and AI are increasingly important in public health, from monitoring and managing pandemics to evaluating broader disease patterns.[73] And the impact of AI in economic contexts is widespread (chapter 6).

Moving forward, we can anticipate increased AI integration in ways that directly affect our physical world or indirectly through informing and augmenting human decisionmaking. Impacts will range from intended consequences to unexpected externalities—and from clearly discernible development impacts to the uncertain and inequitable or those requiring difficult tradeoffs. While digitization's impacts on the physical world date back a generation, applications of AI are distinct in that decisions with real-world consequences will be increasingly made by agents whose behaviour is—to some degree—unpredictable and unexplainable.

AI-infused social networks: What happens when AI makes choices for, between and among us?

Addressing many of today's challenges depends on whether and how we collectively decide to act. These large-scale decisions emerge from how individuals access, interact with, share and act on information.[74] Historically, our collective behaviour depended solely on the nature and structure of interactions between humans—face-to-face or through television, radio and other forms of mass communication. As described earlier, our collective behaviour is entering a new era where social networks will shape human decisionmaking and behaviour at scale, including various artificial forms of intelligence and decisionmaking.[75] The situation today is without precedent in the history of our species and comes when we cannot afford further gridlock or degradation in the ability to manage interdependent crises and challenges.

As we progress, it will be essential to anticipate, identify and manage how artificial intelligence affects collective behaviour, which is a key determinant of our ability to improve human development. How might AI promote collective intelligence, break gridlock and steer our decisions towards sustainability, equity and human flourishing? How might it hold us back? What new interdependent challenges will AI introduce? These big questions will require continual re-evaluation as interactions between humans and AI evolve.

AI can impact how we decide individually and collectively

Scholars since Aristotle have recognized the potential for groups to outperform individuals in decisionmaking.[76] Collective intelligence underscores motivations for democracies, juries, collaborative work and the convening of experts to solve challenges.[77] From a human development perspective collective intelligence can provide individuals access to information and decisionmaking capabilities that exceed what individuals can feasibly achieve independently. Moreover, collective decisions are collective expressions of individual agency—arising from the many choices, values, needs and freedoms of individuals within a group.

> "Because many forms of AI are trained on large swaths of human-generated data, they can be seen as potentially aggregating knowledge across humans in their training set to produce collectively intelligent responses

Broadly speaking, there are two ways in which collective intelligence is harnessed in societal processes. The first involves attempting to elicit a collectively intelligent decision from a crowd through voting, polls, prediction markets or other methods of aggregating opinions.[78] Because many forms of AI are trained on large swaths of human-generated data, they can be seen as potentially aggregating knowledge across humans in their training set to produce collectively intelligent responses. Researchers have begun to evaluate the potential for AI as stand-ins for human crowds in a process known as silicon sampling.[79] Emerging evidence suggests silicon sampling produces responses similar to those of human participants in contexts as varied as voting preferences, numeric estimation tasks and moral assessments.[80] Similarities between the behaviour of AI and humans can reduce the costs of and expand access to polling a crowd while eliminating often exploitative platforms typically used to perform such assessments.[81] While promising, this application of AI to elicit collective intelligence requires some caution. AI cannot retrieve answers missing from its dataset. It can hallucinate, may not perform equally well across knowledge domains and contexts and may exhibit cultural bias or degraded performance across cultural contexts. And accuracy in each context can be difficult to assess, predict or guarantee.[82] Finally, although AI may be able to summarize collective human intelligence, there is no reason to believe it is, itself, collectively intelligent (see box S1.2.1 in spotlight 1.2 in chapter 1).

Where AI and silicon sampling alone are not believed to be sufficiently reliable, AI may be applicable for aggregating information generated by a human crowd. Typical approaches to eliciting collective wisdom from crowds rely on voting strategies, averaging and other mathematical procedures.[83] While well-defined and studied, these forms of aggregation often require boiling down complex decisions into simple sets of options or estimates. Large language models may facilitate collective decisionmaking across more nuanced, natural language–based responses and surface features that might be missed when laying out options.[84] As these approaches improve, they may become valuable techniques for collective decisionmaking, consensus formation and eliciting feedback.

Beyond top-down eliciting wisdom from crowds, collective intelligence also refers to processes that emerge from the bottom up. From the human development perspective our collective decisions are manifestations of our individual agency. To the extent that AI can shape our choices as individuals, it is bound to have consequences for these impactful choices we make as groups. Examples of how collective intelligence facilitates human development are wide-ranging. Individual decentralized contributions over the years to Wikipedia have resulted in a remarkable compilation of knowledge.[85] More generally, constructing and maintaining the open-source software ecosystem are a remarkable feat of human collective intelligence.[86]

But collective intelligence is not a guaranteed feature of groups, and groups can equally become collectively foolish or exhibit behaviour that is sensible in a moment but deleterious in the long run. Classic examples are market panics and mass hysterias.[87] Theoretical and empirical evidence suggest essential conditions are required to promote collective intelligence. Perhaps most fundamentally, at least some crowd members need access to approximately accurate information. Diversity in knowledge, problem-solving strategies and expertise can be critical, enabling collectives to search for a more extensive set of possible solutions when identifying the optimal one.[88]

Beyond diversity the structure of interactions between individuals can be a crucial determinant of success. The benefits of diversity can be lost when individuals holding conflicting opinions exist in echo chambers and cannot bridge the divide.[89] This raises immediate concerns about engagement-optimizing algorithms that disproportionately show content aligned with individuals' pre-existing beliefs or actively create conflict between groups.[90] And large, dense, highly connected networks that are common online can undermine collective intelligence and alter decisionmaking.[91]

> "Taken together, the likely impacts of AI on collective intelligence can be anticipated to be large, varied and highly dependent on whether collective intelligence is being elicited from a group or occurring naturally within it

Taken together, the likely impacts of AI on collective intelligence can be anticipated to be large, varied and highly dependent on whether collective intelligence is being elicited from a group or occurring naturally within it. In a sense, individuals with access to a large language model are tapping into collective intelligence, enabling them to solve problems beyond their current capabilities. Asking questions beyond the training set or for which the model produces inaccurate responses may undetectably lead to the user to tap into collective folly. Yet, in general, AI will likely be a powerful tool for aggregating collective intelligence. While individuals tapping into collective intelligence through AI may improve their capabilities, doing so may homogenize information sources, reducing the diversity that emergent collective intelligence depends on. And filter bubbles, asymmetric influences and dense connections within AI-defined social networks may alter and even reduce emergent collective wisdom that has long been a cornerstone of decisionmaking in democratic societies and institutions.

Once collectives arrive at a solution, it is necessary to coordinate and act. Remarkable examples of successful large-scale collective action range from rapidly responding to the depletion of the ozone layer to eradicating pathogens such as smallpox.[92] But failures to act are also common, as with climate change. A recent survey of 62 countries indicated that belief in climate change is widespread globally (86 percent), as is support for policies to address climate change (72 percent).[93] Yet despite this clear global support substantive progress in addressing climate change has been frustratingly slow, so there are big questions about whether, how and when AI will facilitate or hinder collective action.

Will AI choose our culture?

Collective intelligence and decisionmaking describe emergent properties of collectives that typically occur over short timescales. On longer timescales information flows through collectives, giving rise to persistent norms, beliefs, values, knowledge and other ephemera that shape cultures. The study of cultural evolution focuses on understanding how and why cultures change as cultural artefacts emerge, spread, fixate, dwindle and vanish. Cultural evolution undergirds the success of our species, as ingenuity can be transmitted and refined, enabling us to adapt to changing conditions.[94] In the coming decades cultural evolutionary processes will shape our response and adaptation to a rapidly changing world—and whether those changes sustainably and equitably promote human development.[95]

A key element of cultural evolution is the rate at which new culture emerges through innovation. Coupling human social networks with AI is almost certain to influence the rate and way cultural innovations occur. For one, various forms of AI can create new cultural artefacts autonomously or in conjunction with humans. These can be the products of generative AI, strategies learned in self-play games or innovations such as novel drugs and facilitated insight into scientific problems (see box 2.1).[96] Even purely machine-generated cultural artefacts can diffuse into human culture, such as strategies learned by machines through self-play in the game Go, resulting in drastic differences in play among humans.[97]

AI can disseminate, sort, modify and filter cultural artefacts when acting as an intermediary between humans. In a sense any data-trained model implicitly disseminates the cultural features of its training data. Often, training data are scraped from the open internet so that the available data reflect the history of the digital divide and disproportionately represent individuals from high HDI countries. This can result in large language models adopting the cultural characteristics found in their training set. One recent study found that responses by large language models were consistent with English-speaking, very high HDI countries such as Australia, Canada, New Zealand, the United Kingdom and the United States but culturally distinct from places such as Libya, Pakistan and Tunisia—with countries' cultural differences from the United States correlated with how much ChatGPT reflects the culture of those countries (figure 2.4).[98] Disaggregating these data by HDI level reveals that ChatGPT tends to more strongly reflect cultures in very high HDI countries and less resemble cultures in low HDI countries. This is unsurprising because areas that crossed the digital divide earlier left larger online footprints for training these models. Thus, while technologies such as large language models may foster innovation, they may do so in a way that selectively favours and reinforces views from countries better represented in their dataset. This risks new inequalities whereby closing the digital divide may result in cultural homogenization and net decreases in cultural diversity and innovation.

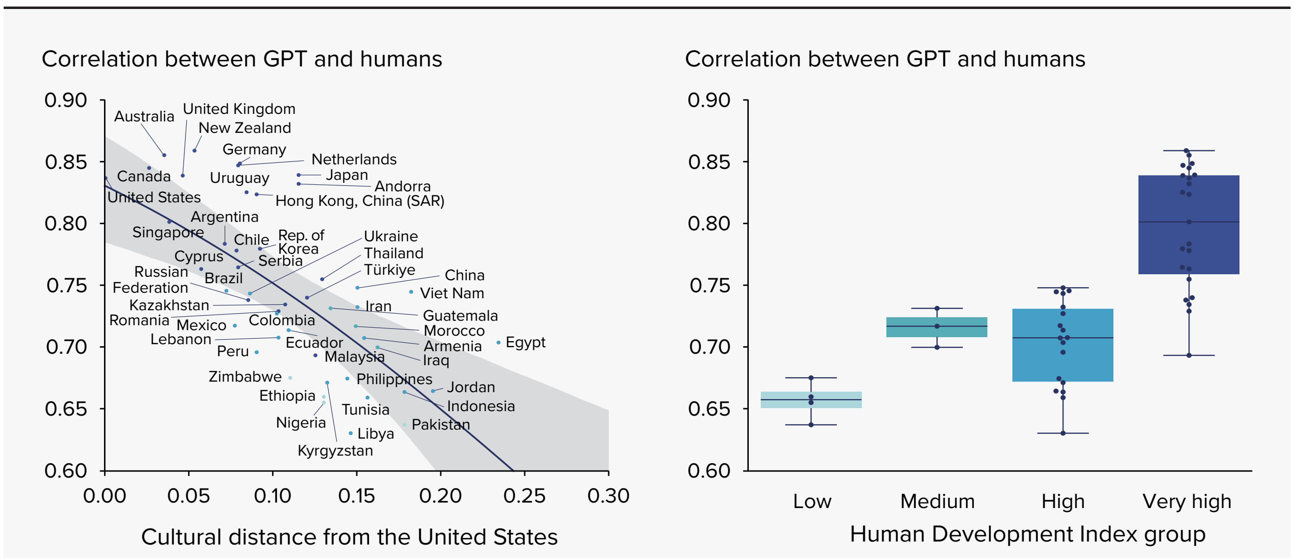
Preserving and expanding human agency across scales

Above, we laid out the dizzying myriad potential consequences of AI for human development, impacting our agency and freedoms both individually and collectively, now and in posterity. Against the breadth of possible impacts, the task of adopting AI in a way that preserves—much less expands—human agency can seem daunting. Even something as trivial and commonplace as a newsfeed recommendation can alter the information on which we base choices as individuals, with emergent consequences on democratic outcomes and in posterity through cultural shifts. If such decades-old ranking algorithms convey these risks, what do we make of the newly expanded decisionmaking capabilities of large language models, or whatever technologies arise in the near term?

This fundamentally changes the calculus as more powerful models come online, because they are not simply "better" but provide a wider range of possible outcomes for agency, ranging from promoting it to undermining it (see figure 2.2). In many cases the best form of AI for a given context may be something simpler that we can understand and that retains agency. In others the newfound capabilities—such as conversing in natural language—may provide ways of restoring and expanding agency (chapter 5). Although AI is no longer well understood as a tool, agenticity itself is a tool we can leverage when appropriate.

This perspective is particularly salient when we consider the emergent consequences of embedding AI into our social networks, from its impacts on collective decisionmaking in the here and now to

Figure 2.4 Cultural differences from the United States explain the use of ChatGPT



Source: Atari and others 2025.

longer-term impacts on cultural selection. If we cede our individual agency to unpredictable AI, we are rolling the dice with human development at scale. However, if AI is designed in ways that promote human agency, we can ensure that humans can steer their future according to their values, needs and goals.

Although this chapter has largely dabbled in the abstract, from it arise more concrete recommendations for deploying AI:

1. *Start with simpler and more tool-like AI. These systems are more predictable,* readily explained and understood, and easier to modify so that our choices remain choices (see table 2.1).

2. *Consider large-language models,* which hold promise as interfaces. Amid the captivating way in which these tools make broad-ranging choices, it is easy to lose sight of their linguistic capabilities and what that means for human development. Literacy and language barriers have befuddled expansion of the promises of digital tools, and these technologies in their current form are capable of drastically reducing these barriers. Choices of how to translate various words or how to convert speech to text likely minimally reflect one's agency—such that adopting technologies to overcome these barriers seems immediately doable and worthwhile.

3. *Automate and change rarely; explain and verify often. Automation risks decisions being made and consequences being accumulated at a rate that precludes humans from weighing in. Similarly,* benefits of nominally "improving" AI on a task should be weighed against risks that changes will lead to different outcomes than people expect. Designing systems so that humans can have time, if they choose, to interrogate the choices the systems make, understand how the systems arrived at those decisions and verify the decisions before actions are taken can ensure that agency remains intact even if choices are automated.

4. *Heed the scale of effects and cultural contexts. AI that is used by institutions or that impacts information flows between people can have outsized effects on the decisions we make and how those decisions shape our future. Scientific and regulatory attention should be paid especially to AI that sorts,* filters and summarizes the information we use to make decisions or that makes decisions for large swaths of individuals.

5. *Do not ignore boring,* tedious and repetitive choices, which may make the best use cases. Not every choice we make expresses our agency to a meaningful extent—some are simply decisions we must make on the path to more important actions. AI already makes many of these choices for us—determining the fastest route to work, showing the correct spelling of a word, identifying and removing scams. More broadly capable AI, emerging every day, often gets coverage for its exciting possibilities—but the boring AI may be among the most agency-expanding.

These recommendations are nonexhaustive but illustrate the clarity provided by centring human agency rather than being distracted by the newest machine. This perspective further alleviates the need to predict what is next for these technologies, from stagnation to artificial general intelligence, and allows us to face whatever comes next by simply asking how it can be leveraged to improve human agency. Perhaps most fundamentally, this perspective restores human agency in a broad way—asking what we can choose to do now, rather than hoping something more agentic will come and choose for us.

CHAPTER

3

Artificial intelligence across life stages: Insights from a people-centred perspective

Artificial intelligence across life stages: Insights from a people-centred perspective

People at each life stage use artificial intelligence (AI) with varying frequency and for different purposes, influenced largely by the institutions they are embedded in. Nearly half of students and a quarter of working people use AI-powered applications more than once a week, primarily for education and work. In contrast, only 15 percent of nonworking people and 9 percent of retired individuals do so, mostly for entertainment and health. These differences in frequency and purpose of use shape the ways in which AI affects people's lives.

The life stage perspective reveals three policy imperatives—the "three I's"—for advancing human development:

Invest in universal access to electricity, internet, digital devices and the skills needed to use them effectively.

Inform people of the risks and opportunities of AI, enabling them to make informed choices about when and how to use it.

Include people of all ages, genders, ethnicities and backgrounds in AI design and development, and bring firms into inclusive policy conversations on how to make AI work for people.

From school computers and teenagers' smartphones to work platforms and advanced imaging in healthcare, artificial intelligence (AI) now plays an integral role in digital technologies. But to what ends? To provide access to information about almost anything? To entertain people? To augment what humans can do and be? This chapter asks whether AI is helping expand people's capabilities to fully realize their potential. It provides insights from a people-centred perspective showing how AI is reshaping people's lives across age groups, changing the way people function and societies operate—thus reshaping human development.[1]

The frequency and purpose of AI use differs across people at each life stage. Almost half of students and a quarter of working people use AI-powered applications more than once a week—mostly for education and work—while only 15 percent of nonworking adults and 9 percent of retired people do so, mostly for entertainment and health (figure 3.1). This is partly because people are surrounded by institutions that vary in the ability to shape AI use.[2] With different use, people are affected differently: their freedoms are not always expanded, and at times they are exposed to risks and challenges. The life-stage approach disentangles some of these effects to show how social, political and economic institutions can enable people to harness AI in ways that expand human development. Within this approach the goal is not to analyse how using AI during one life stage affects the others—because there is not yet enough evidence on this, especially for older people—but to zoom in on each life stage separately to derive policy options tailored to the challenges and opportunities of each age group.

During early childhood excessive use of some digital technologies can have adverse effects on socioemotional development and basic functions—and can even alter brain development—with consequences that may last a lifetime. For many young children, family or private daycare arrangements are the main institutional setting, making an overarching approach to protecting small children in line with the Convention on the Rights of the Child more challenging. This particularly vulnerable life stage needs regulation and the protections stipulated in the Convention on the Rights of the Child from 1989.[3]

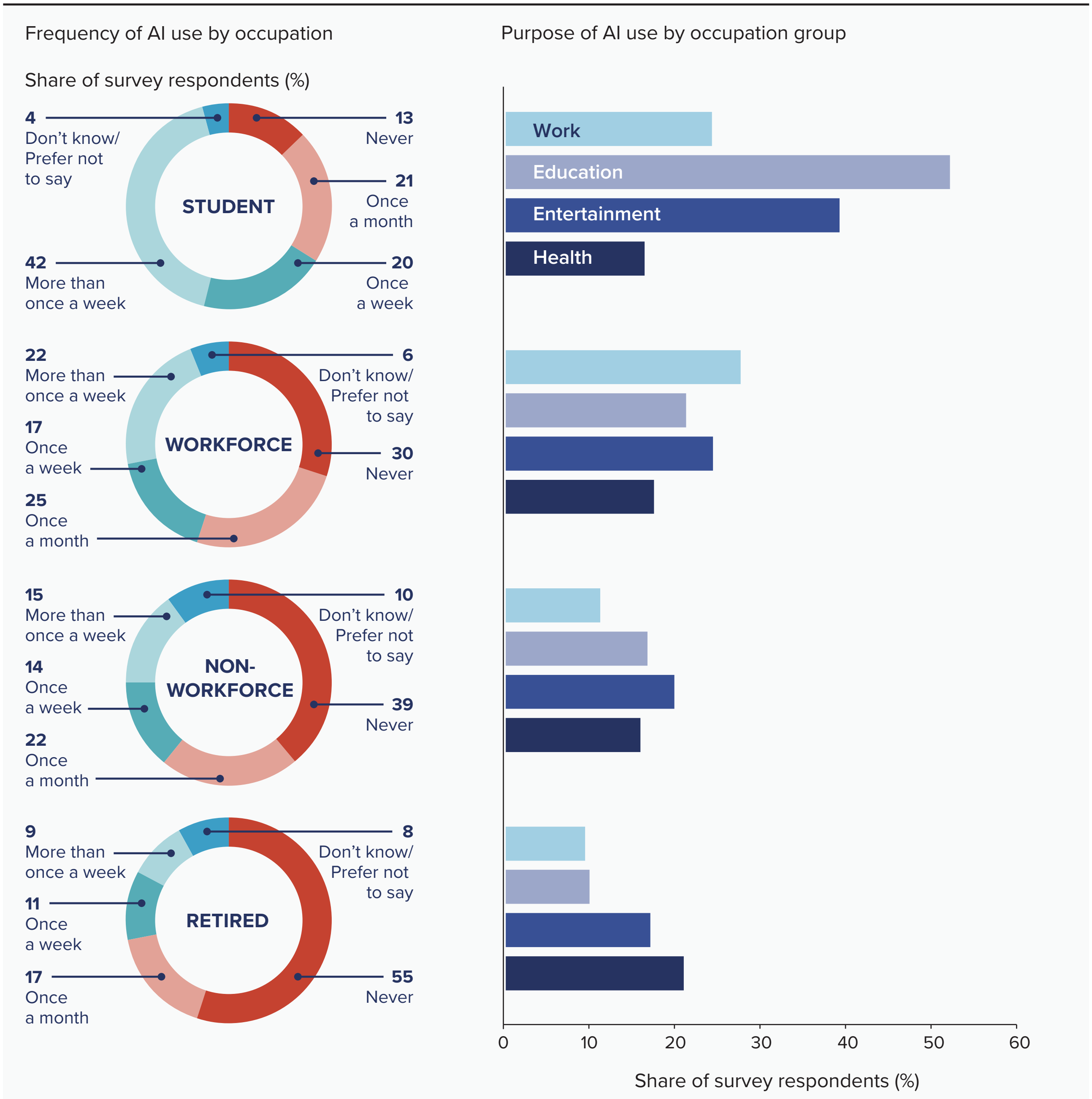
When individuals are in school, AI can enhance learning opportunities and augment teachers' and tutors' work in many ways. Since school-age children spend considerable time in an umbrella institution, capability-enhancing uses of technology are easier to implement through school curricula and practices in the classroom. And AI-powered learning tools can foster equal opportunities for all students, including those with special needs.

Students use AI frequently, mostly for education and entertainment (see figure 3.1). The teenage years involve substantial risk of overuse and even addiction to digital platforms powered by AI algorithms optimized for engagement, potentially exacerbated by AI-supported dialogues and fake images. And with excessive use of social media platforms, there may be adverse effects on mental health, with risks of anorexia, depression and anxiety. Since students use these applications mostly in their free time, safe use depends mainly on oversight by families and other caregivers, potentially amplifying inequalities in society.[4] For social and emotional wellbeing, rapid responses from institutions have to keep up with technological developments.

People in adult life have multiple overlapping identities, each involving different uses of AI. In professional life AI may increase productivity and augment what workers can do, but if it is biased towards automation, it can also mean job losses for incumbents. Parents have a substantial role in modelling and teaching the responsible use of new technologies, and friends and partners may engage in synthetic relationships with AI-powered companions. Although adults also frequently use AI for entertainment (see figure 3.1), they appear better equipped to regulate their emotions and behaviour, given their brain and body development.[5] Still, concerns remain about autonomy, authenticity and agency as recommender systems may shape preference formation and decisionmaking.

Generally, older people who did not grow up with modern technology are more critical of AI and use it less frequently (see figure 3.1). Communication apps and promising AI-facilitated tools in the health sector, which older people use the most, can reduce social isolation and improve physical wellbeing, but older people's needs and preferences must be part of these products' design. Human connections and options, such as having the possibility of interacting with a person rather than an automated service, are keys to expanding their freedoms in this digital age.

Figure 3.1 People at each life stage use artificial intelligence (AI) with varying frequency and for different purposes



Note: Based on pooled data for 21 countries. For purpose of AI use, the following responses to the question, "In the past 30 days, have you ever interacted with artificial intelligence, such as chatbots, in any of the following ways?" were used to calculate the average use of AI for work, education, entertainment and health: "work" is based on the response "work-related tools or software," "education" is based on the response "educational platforms of learning apps," "entertainment" is based on the response "entertainment (e.g. streaming services/gaming)" and "health" is based on the response "health care services or applications." For frequency of AI use, the question was "How often have you used artificial intelligence tools such as ChatGPT, Google Gemini, Microsoft Copilot, etc., in the past 12 months?" and allowed for a single response. For occupation group the following responses to the question "What best describes you? Are you...?" were used: "working" includes self-identified full- and part-time employees and self-employed respondents, and "not working" includes homemakers and unemployed respondents.
Source: Human Development Report Office based on data from the United Nations Development Programme Survey on AI and Human Development.

Which policies can help harness AI to expand human freedoms, enhance agency and foster human development? The human development framework provides some guiding principles for decisionmaking. The chapter identifies three policy imperatives for all life stages: invest, inform and include. Investing in universal

Figure 3.2 Invest, inform and include for people-centred artificial intelligence (AI)

- **INVEST** in AI technology that protects children's rights in the digital space.
- **INFORM** parents, paediatricians and caregivers about risks related to young children's digital technology use.
- **INCLUDE** the private sector in working groups on children's rights and protection.

- **INVEST** in universal access to digital devices and AI in classrooms.
- **INFORM** about potential biases in AI systems and prevent the stifling of creativity and critical thinking.
- **INCLUDE** responsible use of AI in school curricula, emphasizing skill development.

- **INVEST** in public-private partnerships to make AI-powered social media safe for adolescents.
- **INFORM** about AI-powered social media's addictive features and susceptibility to social comparison.
- **INCLUDE** adolescents in the critical evaluation of social media and other AI-powered products.

- **INVEST** in subsidies for companies that offer human options to make sure nobody is left behind.
- **INFORM** about role modeling responsible AI use to influence future generations.
- **INCLUDE** explanations about how AI products and algorithms work to strengthen adults' agency.

- **INVEST** in access, training and support for older adults to empower them to navigate AI applications.
- **INFORM** older people about AI innovations, highlighting applications in their areas of interest.
- **INCLUDE** older people in the development of AI products so that their needs are adequately reflected.

Source: Human Development Report Office.

electricity, internet devices and digital skills can expand individual capabilities by facilitating access to AI and the ability to use it effectively. Informing people of when and how to use AI can expand their functionings and help them fully realize their potential. Including people of all ages, genders, ethnicities and backgrounds can allow them to align their choices with their values and thus exercise their agency (figure 3.2).

Early childhood—too little, too much, too risky

The impact of digital technologies on early childhood development is a topic of hope and concern as societies around the globe become more digitally connected. The effects of screen time—associated with many AI applications used by toddlers—can be both positive and negative for young children's emotional, cognitive and physical development. The type of activity and its duration determine the actual impact. Very young children spend most of their time at home with family members or in private daycare.[6] So, ensuring that AI technologies are development enhancing is essential; otherwise, the consequences for brain development can be severe. Indeed, impaired brain development can limit human freedoms throughout life, impeding choices, capabilities, agency and thus human development. And even without screen time children's vulnerability is reflected in the online sphere, multiplied by new AI-powered tools (box 3.1).

Young brain structures change with too much screen time

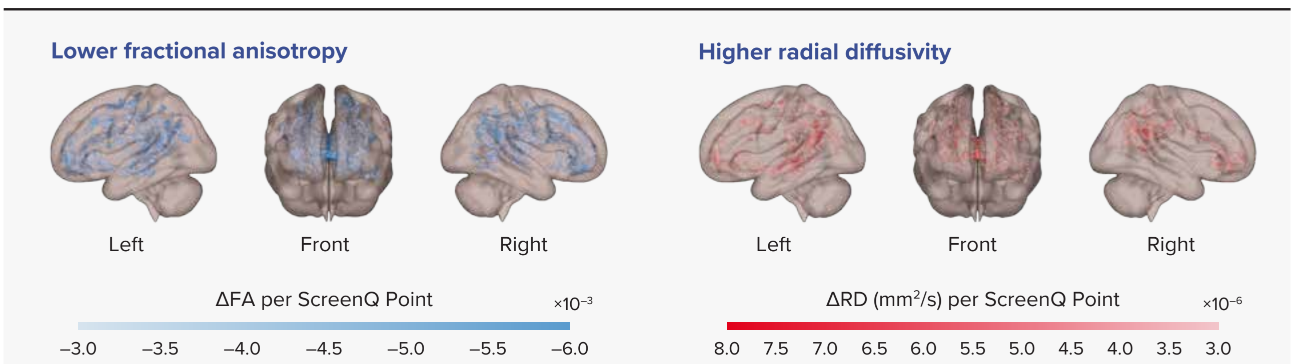
Toddlers' use of AI often involves a screen, and interactive screen time can deliver benefits. For example, the right software and environment can improve early childhood learning, including vocabulary, numeracy and digital skills that improve later academic performance.[7] But these benefits occur only when used for a very limited amount of time.

Excessive screen time can lead to a range of developmental issues, especially emotional and behavioural problems, such as hyperactivity, low attention span and peer problems.[8] It can also lead to delayed developmental milestones, impaired motor skills and decreased executive functioning—higher cognitive processes that help with planning, organizing, problem solving and self-regulation. And it can lead to inappropriate conduct, reduced physical activity, poor language skills and limited vocabulary, especially at a very young age.[9] Vocabularies can be assessed through cognitive testing and monitored using diffusion tensor imaging, which visualizes brain changes associated with excessive screen time (figure 3.3).[10] Violent video games are a major risk, since they can exacerbate aggressive behaviour, reduce empathy and diminish prosocial behaviours.[11]

Most findings come from local or national studies because of a dearth of globally comparative data on developmental milestones. Attention-deficit/hyperactivity disorder (ADHD), diagnosed according to similar criteria all over the world, is used as a proxy for hyperactivity and low attention spans in children. And although ADHD is more complex, including other symptoms such as impulsiveness,[12] its prevalence across countries can shed some light on the relation between screen time and ADHD symptoms. Several recent studies suggest that, in addition to genetics and other behavioural factors, excessive screen time during early childhood can play a role in ADHD. But children with ADHD might be granted more screen time because their condition makes supervising them more challenging.[13]

The implications of excessive screen time and lack of access to screens on the brain development of future generations both seem profound. Examples

Figure 3.3 Excessive screen time in early childhood is related to changes in the brain structure—and to reduced language capacity and understanding

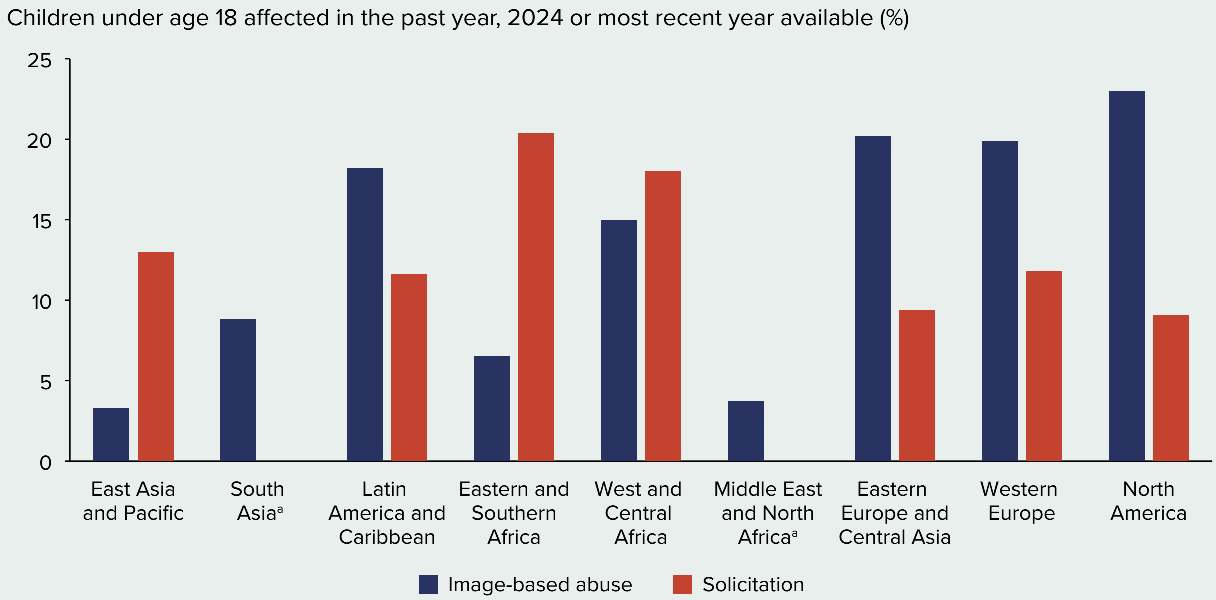


Note: The figure depicts diffusion tensor MRI scans of preschoolers' brains that show the decline in fractional anisotropy and the increase in radial diffusivity, both of which are crucial for language understanding and capacity, as screen use rises. Darker colours indicate more change. Screen use is measured by ScreenQ, a 15-item measure of screen-based media use reflecting the domains of the American Academy of Pediatrics recommendations: access to screens, frequency of use, content viewed and coviewing. Higher scores reflect greater use.
Source: Hutton and others 2020.

Box 3.1 **Artificial intelligence can violate children's rights—or protect them**

Online child sexual abuse can take several forms, from sharing sexual images or videos to online solicitation consisting of unwanted or pressured sexual interactions.[1] Such abuse is common even in regions with low access to digital technologies (box figure 1)—and sharply on the rise in many African countries.[2] While solicitation is more common among adolescents, most image-based abuse (around 85 percent) affects prepubescent children, including infants and toddlers.[3] The younger the child, the more severe the abuse.[4] The majority of images show female children.[5] Abusive images are refined and reproduced by artificial intelligence (AI)–powered apps, multiplying the violations of children's rights.[6]

Box figure 1 **Online child sexual abuse occurs even in regions with low access to technology**



a. Data on solicitation are not available.
Note: Image-based abuse includes all nonconsensual taking and sharing of sexual images and videos of a child, as well as unwanted exposure of a child to pornographic materials. Solicitation covers a range of unwanted and pressured sexual interactions, including sexual inquiries over mobile phones or the internet, as well as long-lasting sexual conversations that can lead to exchanges of sexual pictures or videos.
Source: Human Development Report Office using data from Childlight (2024).

AI can allow the massive production and dissemination of material that violates children's rights, including fake images and AI-generated images based on "famous" abuse victims.[7] But it can also augment humans' analysis of images and video to flag potentially harmful content for further review.[8] Unlike hashing technologies that rely on exact data matches, such as PhotoDNA,[9] AI algorithms are adaptive and can be trained to detect harmful images by recognizing patterns in the data.[10] This approach can increase the detection rate of harmful content over human intervention alone and helps prevent the repeated sharing of prohibited images, thus reducing the revictimization of the children depicted in the content.[11] AI-facilitated tools can also assist in identifying and tracking perpetrators. By analysing patterns of online engagement, AI algorithms can provide useful information to locate creators and distributors of harmful material.[12]

Article 4 of the United Nations Convention on the Rights of the Child obliges signatories to introduce laws and regulations that prevent companies from infringing on children's rights, to monitor their compliance and to ensure effective enforcement and remedies for child rights violations.[13] The United Nations Guiding Principles on Business and Human Rights and the Children's Rights and Business Principles provide a framework to meet responsibilities towards children's rights.[14] The Global Digital Compact solidifies states' commitment to protect children's rights in response to emerging technologies and their associated opportunities and risks.[15] Governments and private companies should collaborate and invest in AI-facilitated tools to augment humans in detecting and deleting content harmful for children.

Notes
1. Childlight 2024. **2.** ChildFund International and African Child Policy Forum 2024. **3.** INHOPE 2023. **4.** ECPAT and INTERPOL 2018. **5.** In one sample as much as 99 percent of images were of girls (IWF 2024). See also ECPAT and INTERPOL (2018). **6.** IWF 2024. **7.** IWF 2024. **8.** Amlani 2024; Anglia Ruskin University 2024; Child Rescue Coalition 2024; Grzegorczyk 2023; IWF 2023, 2024; Krishna, Dubrosa and Milanaik 2024; Singh and Nambiar 2024; US Department of Homeland Security 2024. **9.** Allen 2011. **10.** Grzegorczyk 2023. **11.** Allen 2011; Fry 2024; Grzegorczyk 2023. **12.** Grzegorczyk 2023. **13.** Pothong 2025; United Nations 1989a. **14.** UNICEF 2012; United Nations and UNOHCHR 2011. **15.** United Nations 2024.

from countries that have had widely diffused digital technologies for years can make evidence-based information more compelling, generating important messages for policymaking in countries where digital technologies are not yet as widely available.

As digital access expands globally, a task for governments is to roll out campaigns that inform parents, paediatricians, teachers and other caregivers about the adverse effects of excessive screen time. Screens are sometimes used when parents are actually in need of childcare—for example, when they are working remotely or busy with other tasks around the house. This should reinitiate a conversation about affordable and flexible childcare. Community-level programmes can offer valuable alternatives, with flexible times and signups.

School age—access, regulation and ownership

Whether AI benefits or harms school-age children depends on how institutions regulate and inform their use. Access to the internet has helped advance children's learning in recent years. But since AI has come into play, new and challenging questions have emerged. What about the risk that children who use AI for schoolwork lose out on interpersonal skill development? Since most school-age children are enrolled in some type of formal education, social and political institutions have a more direct influence on their technology use, which makes it easier to mitigate risks and enhance benefits.

AI in the classroom—inequality rising, declining or both?

AI's potential for expanding students' capabilities through education is becoming more evident for those who have access to it. AI-powered apps can provide study assistance when educators or parents face time or resource constraints.[14] They can gamify the study experience to motivate students.[15] And they can improve personalized learning by tailoring educational content to individual student needs and predicting their next learning steps.[16] AI could thus level the playing field for disadvantaged students and bridge education gaps in the light of constrained resources. Fascinating advances have also been made in using AI to support disadvantaged students (box 3.2). It also holds promise in aiding interventions to reduce school dropout rates, especially in low-income countries, where such rates are high.[17] For that, however, universal access to digital technologies is paramount.

Inherent biases in AI systems, particularly from the perspectives and backgrounds of their developers, can exacerbate inequalities between racial, ethnic and religious groups.[18] There are also ethical concerns about privacy, security and responsible AI use.[19] At the AI Academy in Tajikistan,[20] students and teachers developed a machine learning–based credit-scoring product for microloans that outperformed scoring systems used by other banks in the region.[21] But AI in credit scoring raises concerns about data privacy, potential algorithmic bias and lack of transparency in decisionmaking. Ethical considerations of fairness, accountability and responsibility also require careful attention.[22]

Constant vigilance and policy attention to embedded biases can prevent discrimination. By purposefully building and deploying AI-powered tools with these considerations in mind, the benefits can be harnessed without unintentionally increasing exclusion.

And what happens to skills?

While AI has the capacity to tailor learning experiences to individual student needs, concerns have emerged about its potential to stifle creativity and other essential skills. AI could facilitate overemphasis on standardized testing and overshadow crucial abilities such as creativity, collaboration and critical thinking.[23] Some of these soft skills, also linked to emotional intelligence, will become more important as AI becomes better at routine text and data analysis.

Using AI-powered chatbots for schoolwork could also undermine opportunities to learn skills such as analysing text, elaborating syntheses and writing coherent narratives. The writing process stimulates thinking, scrutinizing and self-improvement, tasks that all students should learn. But when it is outsourced to AI-facilitated tools (cognitive offloading), the reduction in cognitive effort can reduce

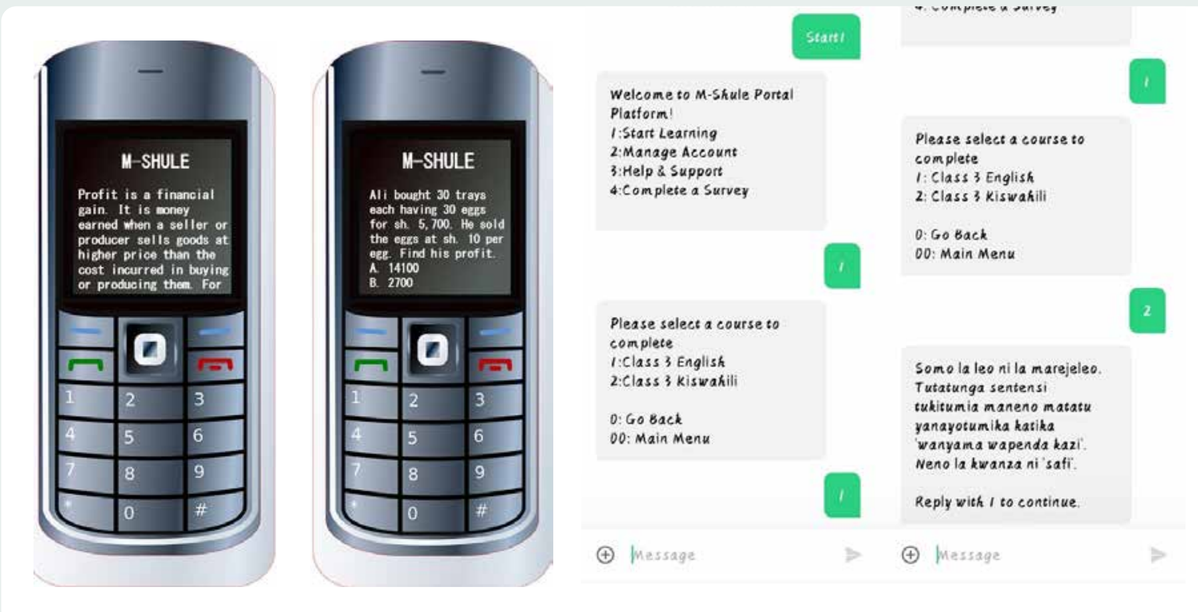
Box 3.2 Levelling the playing field for disadvantaged students

Innovations in artificial intelligence (AI) could boost the capabilities of students facing disadvantages during their education journey. Migrant children, for example, can face language barriers and different stages of learning when joining their host country's education system.[1] AI has addressed both, offering real-time voice-activated translations and individually tailored educational resources, translated into several minority languages.[2] Similar tools can be used in refugee camps to adapt instructions to individuals with diverse education backgrounds, though major challenges include children's digital illiteracy and the costs of running AI-powered programs.[3]

An educational platform in Kenya uses AI-facilitated adaptive learning engines to assess student performance and provide tailored lessons in several languages (box figure 1). It has reached more than 20,000 children,[4] even students without access to the internet, with personalized lessons, questions, remedial learning and evaluation through SMS.[5] The platform reduces language barriers by including minority languages not typically covered in the standard education curriculum and languages spoken by refugees from neighbouring Somalia and South Sudan.[6] It operates in the most challenging learning environments, such as slums in Nairobi and the rural Dadaab refugee camp.[7] It also offers microcourses on business and entrepreneurship for youth and adult refugees and courses on employability skills for youth with physical, hearing and visual impairments.[8]

This and similar platforms rely on collaboration and funding from international organizations, development agencies and nongovernmental organizations to purchase and distribute its products. Public-private partnerships are essential to deploy these technologies where they are needed most.

Box figure 1 Artificial intelligence tailors lessons, even for students without internet access



Source: Human Development Report Office, adapted from M-Shule (2023b).

Notes

1. Drolia and others 2022. **2.** UNESCO 2019. **3.** Tzirides 2022. **4.** UNESCO 2022. **5.** UNESCO 2022. **6.** M-Shule 2023a. **7.** UNESCO 2022. **8.** M-Shule 2023b.

memory retention and diminish learning and cognitive abilities.[24] Learners may remember only where they stored information but fail to integrate it into their brain's secondary knowledge. This can create an illusion of having learned the information, increasing the risk of memory manipulation or corruption.[25]

Increasing or perpetuating inequalities is also a risk. Since individuals who believe they have a limited memory capacity tend to offload information more frequently, their knowledge deficit can widen, possibly reducing their learning performance over time.[26] Even students are worried that AI-powered chatbots, although convenient, diminish their writing skills and hamper their motivation and drive to compose on their own.[27]

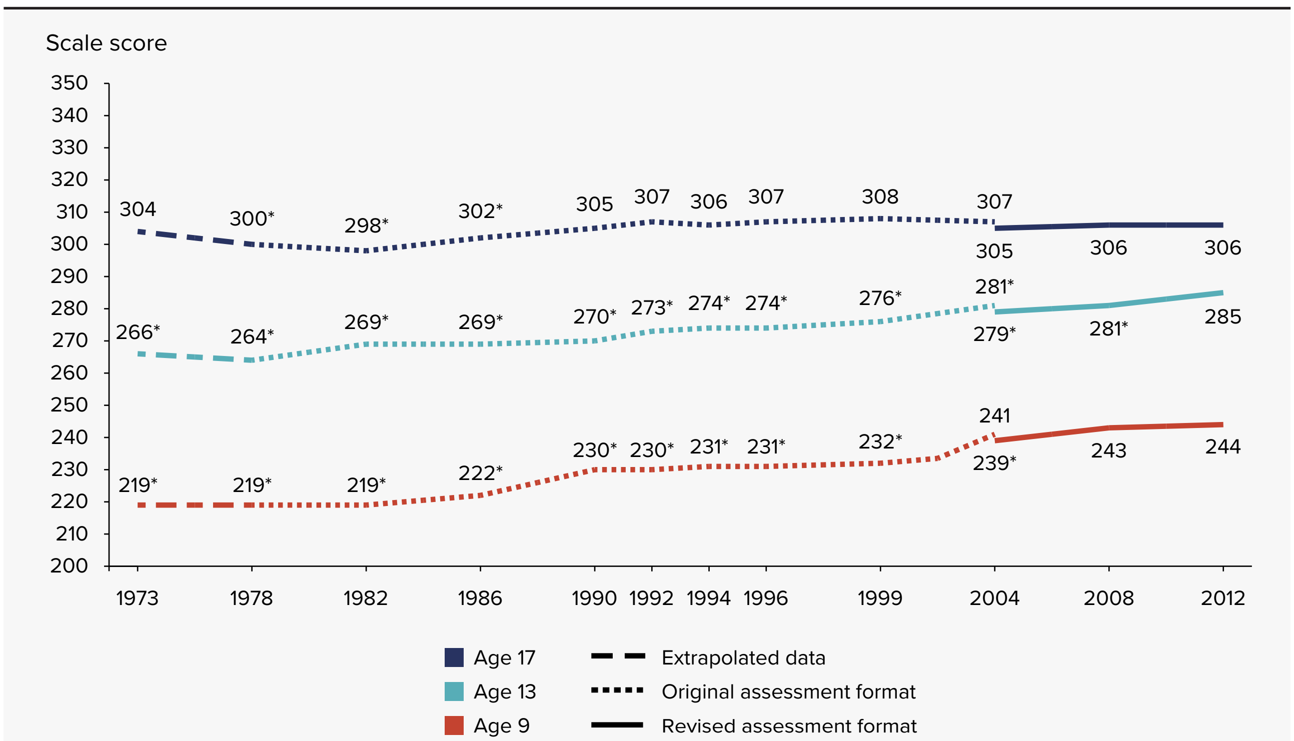
Concerns about calculators diminishing math skills were similar. Released to the public in the early 1970s, the first handheld calculator was expensive. Once readily available in all classrooms (around 1980 in the United States), mathematics achievement was expected to decline—this was not the case, however; it even improved slightly (figure 3.4).[28] The reason is believed to lie in the level at which calculators are used in school—usually not earlier than middle school, when fundamental mathematics skills should have already been acquired. After this milestone using a calculator can lead to higher student achievement.[29] The implication could be the same for AI-powered chatbots: once students have acquired basic writing and text analysis skills, the chatbots could improve the learning process through review and feedback, accompanied by a teacher or other caregiver.

However, a base of knowledge is required for the brain to refer to during creative or critical thinking. These higher-order thinking skills are essential for problem solving and can be developed only if the brain can retrieve facts and figures from past learning processes.[30]

And to social interactions?

If used excessively in education, AI can put at risk valuable human connections and the sense of community in the learning process.[31] Since machines lack the empathy hormone, oxytocin—which can "couple two brains" in such a way that they are linked to each other, making learning more efficient—AI is biologically unable to perform some features of teaching.[32] This is one of many reasons why teachers cannot be substituted for or even replaced by AI (chapter 1). Instead, AI-powered apps and programs

Figure 3.4 Mathematics achievement in the United States did not decline after calculators became available in the classroom



* Significantly different from the 2012 value at $p < .05$.
Note: Extrapolated data adjust for the limited number of questions that the 1973 mathematics assessment had in common with later assessments. Original assessment format uses the same assessment procedures established for the first assessment year. Revised assessment format incorporates more current assessment procedures and content.
Source: US National Center for Education Statistics 2013.

can be complementary tools under close teacher or caregiver supervision or can help teachers with other tasks, allowing more time for student interaction (chapter 2). As AI continues to permeate education, its benefits and potential drawbacks should be continually monitored by interdisciplinary teams of educators, neuroscience researchers, policymakers and other stakeholders to ensure that future generations are well-equipped for a world increasingly intertwined with technology.

Some concerns about children's interactions with different forms of AI are similar to more traditional concerns about the use of digital devices—for example, substituting offline activities such as playing together outside with social interactions in the online space, as well as disinformation and security of personal information, especially in the light of sophisticated and adaptable AI-powered conversation partners.[33] Other concerns are specific to the new possibilities of interacting with AI, such as developing social etiquette.

Digital assistants do not yet teach good manners or require politeness, so children may eventually get used to an undesirable form of communication when interacting with humans.[34] Again, that is why digital technologies should complement but not substitute for humans, especially around children. The good news is that when interacting with digital voice assistants, children identify them as machines and sources of information, at best as social learning partners, but do not accord them the same value as humans.[35] Children reveal less information when interacting with the devices and are more influenced and engaged when interacting with humans.[36]

Social interaction is at the core of human learning, since problem-solving skills are greatly improved through implicit communication, such as imitating others. Correctly interpreting others' mental state to understand their knowledge and intent is a major factor in wellbeing and in the ability to navigate the world of work, whether in the labour market or personal affairs. It is best learned when practiced with empathetic human beings.[37] An experiment in a nature classroom showed that students who had been away from screens for five days improved their recognition of nonverbal emotional and social cues more than their peers who had not been away from screens. Time away from screen-based media and digital communication tools improved both emotional and social intelligence.[38]

Adolescence—smartphones, AI-powered apps and mental wellbeing, much ado about nothing?

Although most adolescents still participate in some form of official schooling, this stage of life deserves a separate section from school age, given the profound neurobiological, behavioural and environmental changes that affect how adolescents interact with AI-powered apps.[39]

Buzzing controversies among researchers, politicians and caregivers have emerged about whether smartphones have a negative impact on young people's wellbeing. Empirical evidence points to a concerning decline in subjective wellbeing, which is also reflected in a rise in indicators that measure mental disorders, such as anxiety and depression.[40] The effect has been particularly strong for young women.[41] The sharp decline in wellbeing has altered what was commonly known as the U-shaped curve of wellbeing throughout the life course: life satisfaction was highest at young age, then dipped during middle age and rose during old age (spotlight 3.1).[42] These changes have gone hand in hand with the increasing use of smartphones among the wider public, especially in countries with very high Human Development Index (HDI) values, although the causal mechanisms underlying this relationship are not fully established.[43]

Less is more, and quality matters

What lies behind this association? Should parents try to ban smartphones during adolescence altogether? The evidence is mixed, partly because not all studies disaggregate for age, which seems to be crucial for the effects of smartphones on wellbeing.[44] AI algorithms that make recommendations on social platforms based on online behaviour and optimized for engagement have addictive potential. And that can trigger sleep deprivation, pervasive social comparisons, lack of physical exercise and social isolation caused by tradeoffs between time spent online and time spent socializing in person, leading to a decline in wellbeing.[45] Excessive use of certain social media increases upward social comparison, which reduces subjective wellbeing indicators such as life satisfaction, self-worth and self-esteem.[46] And even in the absence of addiction or enjoyment, young people may feel pressured into using certain platforms, because most of their peers do (spotlight 3.2).

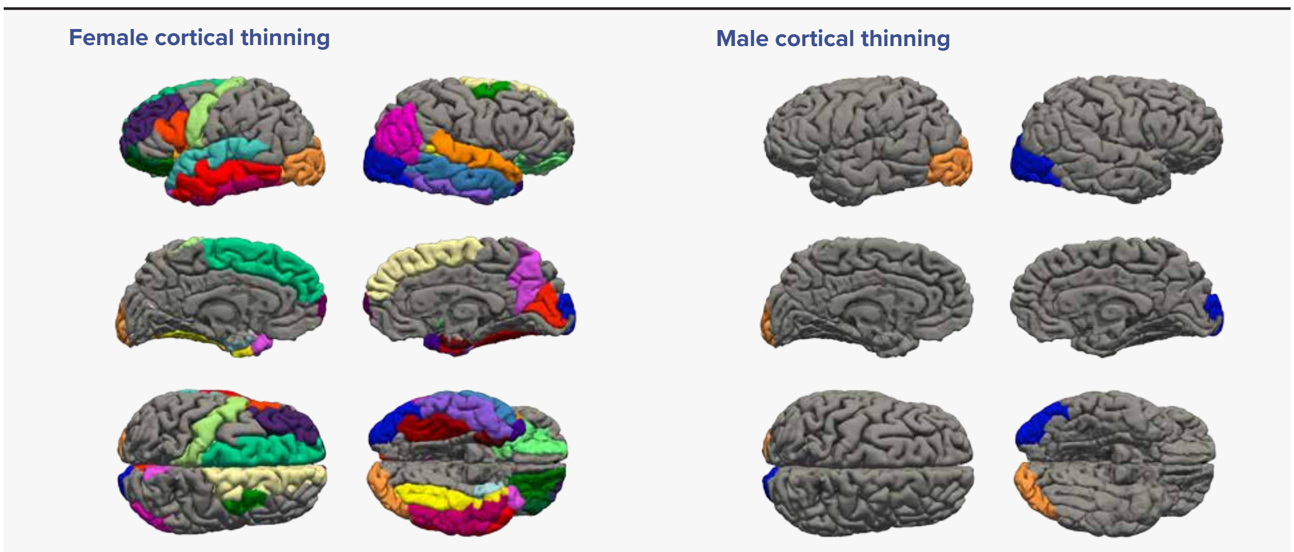
Since adolescents are especially vulnerable to socioemotional disorders given the developmental changes in behaviour, cognition and neurobiology occurring at their age, they are also more susceptible to social comparison, modifying self-images, social feedback, stress and reward mechanisms.[47] With the development of increasingly sophisticated AI technologies, several facets of social media can be especially perilous for adolescents—particularly for young women, who are often more susceptible to social comparison and idealization of body images than their male counterparts (box 3.3). Moreover, specific characteristics of the digital environment contribute to online disinhibition, leading individuals to exhibit different behaviours, thoughts and emotions in online interactions compared with in-person settings.[48] All of this points to the need for careful evaluation of the effect of smartphone use, especially social media, on wellbeing among adolescents.[49]

But other factors—such as genetics, a lack of strong relationships or adverse childhood experience, including abuse, neglect and trauma—are at least equally strong determinants of mental health and wellbeing.[50] A complementary explanation for declining mental wellbeing in the past five years could be related to the Covid-19 pandemic. Recent brain images from adolescents reveal accelerated cortical thinning—a sign of a maturing brain—more notable in females than in males (figure 3.5). This process is attributed to chronic stress and adversity during development, a hint at the life disruptions during lockdowns. Cortical thinning, while not necessarily bad, is associated with higher anxiety and depression rates. The difference between males and females can be accounted for by females' stronger social connections and reliance on sharing stress-related events with peers.[51]

Some online activities that use AI algorithms, such as educational programs and music apps, can be beneficial without being addictive.[52] Young people who already have mental health issues use their phones, or the internet in general, more often and in different ways from their peers.[53]

The bottom line: not all adolescents will necessarily develop depression or anxiety when excessively using a smartphone or being on social media. Young people with pre-existing mental health issues or vulnerabilities are more likely to do so, especially when using social media with AI-powered recommender systems.[54] Screen access should always be

Figure 3.5 Pandemic-related stress is a complementary explanation for adolescents' mental illbeing



Note: Regions with significantly accelerated cortical thinning in the adolescent female and male brains after the Covid-19 pandemic are shown in colour.
Source: Corrigan, Rokem and Kuhl 2024.

Box 3.3 Artificial intelligence on social media undermines agency and drives emotions—but only for some young people so far

The growing prevalence of social media recommender systems optimized for engagement based on online behaviour; of AI-powered photo filters, chatbots and editing tools; and of artificial intelligcen (AI)–generated content such as deepfakes poses potential risks to mental wellbeing. The risk is especially high for young people, as they are the primary users of social media and are more vulnerable to peer pressure than other age groups.[1] Problematic social media use is a strong predictor of psychosomatic complaints and low life satisfaction in 15-year-olds across 37 countries. With excessive social media use, the odds of having psychosomatic complaints rise by about 39 percent, and life satisfaction falls by 33 percent.[2] Even so, some aspects of social media—such as searching for peer support, using platforms as creative outlets and improving connectedness to friends—have positive effects on mental wellbeing.[3]

Social media recommender systems optimized by AI for engagement based on online behaviour provide a passive audience experience, undermining users' agency to curate the content they consume (chapter 5). These algorithms can drive emotions by determining the content users are exposed to.[4] The best example is doomscrolling, a relatively new concept that describes the habitual search for negative news on social media. Once started, AI algorithms will automatically show doomscrollers more and more negative news and content. Doomscrolling is associated with lower indicators of mental wellbeing and life satisfaction.[5]

It can destroy relationships...

AI-generated deepfakes in online cyberbullying and harassment among young people are on the rise and have already damaged relationships among peers. AI can generate realistic-looking images of a person and place them into fake settings.[6] Cyberbullies have used deepfakes to superimpose images of teenagers into inappropriate settings, making it look as if they were nude, drinking underage and vaping.[7] This purposefully misleading content can cause fear, helplessness, suicidal ideation and other mental health issues, especially among young women.[8] The newly adopted Artificial Intelligence Act by the European Union promises regulation of deepfakes, which will have to be labelled as such, once fully implemented and enforced.[9]

and trigger mental health issues...

The growing popularity of AI photo filters producing "thinspo" (inspirational images promoting an "ideal" body type) create unrealistic beauty standards and body dysmorphia. Together with discussion threads and AI-generated harmful information on overly restrictive diet plans, vomiting-inducing drugs and other techniques, vulnerability to eating disorders has increased substantially. And although safety features are improving, so-called jailbreaks (inserting words and phrases to bypass safety features) still allow access to the most harmful content with relative ease.[10]

Discussions have also glamourized depression, suicide and other mental health issues.[11] Subcultures and niche communities have emerged, using codewords to overcome flagging from social media platforms. In just 36 minutes, a bot that interacted with videos centred around depression was shown a TikTok feed where 93 percent of content was sad or depressive.[12] Although most social media firms are making efforts to hide or delete potentially harmful posts, more work is needed to make them more effective. On average, only 15 percent of reported posts with suicidal or self-harm content are deleted, revealing widespread noncompliance with the EU Digital Services Act, which aims to protect young people from harmful content on social media.[13]

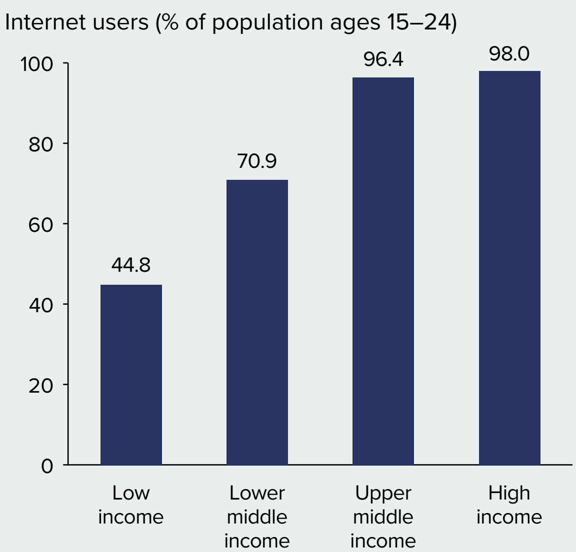
but has done so only for some young people so far

So far, young people in many low- and middle-income countries have been mostly spared these detrimental effects because internet use remains very limited (box figure 1).[14] But if the current trend of swiftly increasing usage persists, it is only a matter of time until young people in these countries catch up (box figure 2). So, the harmful effects of social media on young people will also expand, most likely more than proportionally, because people with internet access in low- and middle-income countries spend more time on social media than their counterparts in high-income countries.[15] There is thus a unique learning opportunity for lower-income countries to skip some of the detrimental effects of AI-powered social media by providing information about risks and guiding the purpose and frequency of use.

(continued)

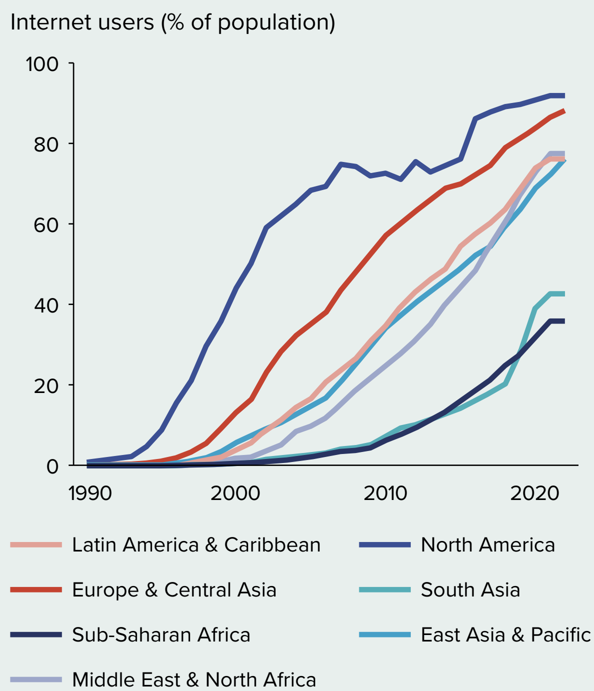
Box 3.3 Artificial intelligence on social media undermines agency and drives emotions—but only for some young people so far *(continued)*

Box figure 1 Most young people in high- and middle-income countries use the internet…



Note: Data are for the most recent year available.
Source: Human Development Report Office using data from ITU (2024b).

Box figure 2 …but others will catch up soon if trends persist



Source: Human Development Report Office using data from World Bank (2024a).

Notes
1. Shah and Bilal 2022. **2.** Walsh and others 2020. **3.** US Office of the Surgeon General 2023. **4.** Kang and Lou 2022. **5.** Satici and others 2023. **6.** Hinduja 2023. **7.** Hinduja 2023. **8.** Laffier and Rehman 2023. **9.** European Parliament 2023a, 2023c. **10.** Bahnweg 2023; CCDH 2023. **11.** Ahuja and Fichadia 2024; Bahnweg and Omar 2023. **12.** WSJ Staff 2021. **13.** Tagesschau 2023. For more detailed information, see three studies carried out by Reset (2023). For more information on the Digital Services Act, see European Parliament (2023b). **14.** ITU 2024b. **15.** Datareportal 2024.

limited to certain times of the day to avoid crowding out healthier activities such as sports, music, creative and nature-based activities and in-person interaction with friends and family.[55]

Teach, fund and collaborate with the private sector

Empowering young people to use AI wisely and feel ownership of their digital experience is a challenge. While schools and other educational institutions cannot control the content of apps or time spent on smartphones outside school hours, they can double down on teaching responsible and metered use. Including AI, algorithms and social media use in school curricula is key to empowering young people to benefit from technological advancement, not suffer from it. Considering rapid technological change, curricula need to be constantly updated and teachers trained to cover the most recent developments—such as deepfake images and AI-generated dialogues, which can be difficult to detect, even for adults.[56] Policymakers could work on regulations for labelling AI-produced content.

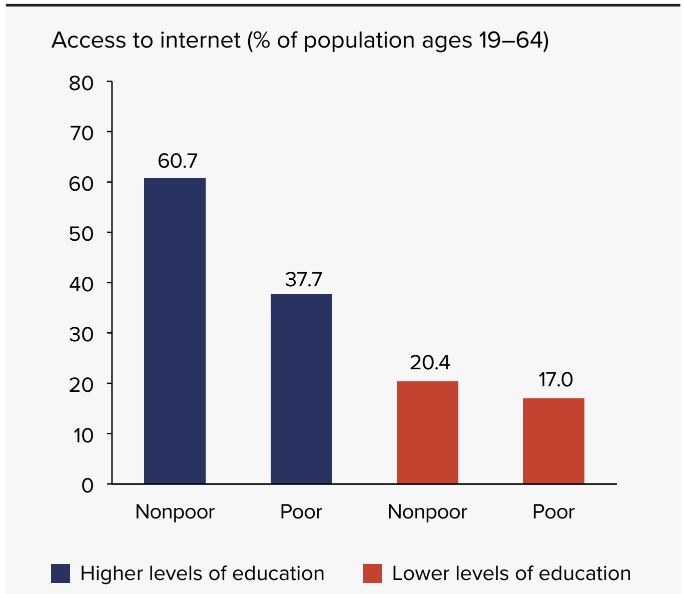
In some cases, AI can help protect young people and their interactions in the digital space. For instance, an automated classification model can identify cyberbullying by analysing text on social media with the help of a deep decision tree classifier.[57] And plugins can educate young people on the critical and responsible use of social media. Virtual learning companions can help young people detect risks and toxic content, building cybercourage and resilience.[58] Creating universal access to these protective technologies is an essential task for policymakers, working closely with private companies. Public-private partnerships could help, as could subsidies for innovative technologies. Funding with strings attached can incentivize the development of products that foster young people's wellbeing, especially when working with smaller tech companies and startups.

Semi-autonomous adulthood—with overlapping identities

Following Amartya Sen's concept of "plural identities," people are not reducible to one single identity.[59] They are employees or entrepreneurs, spouses or partners, consumers or vendors, friends or neighbours—and most likely combine these identities in different ways. So, their experience with and use of AI is also multifaceted, as they act and interact in a variety of institutional settings. For employers and entrepreneurs AI can boost productivity by either increasing product innovation or making production processes more efficient but could put jobs at risk if there is a bias towards automation (chapter 6). Depending partly on policy choices, AI can either compromise or support worker agency (spotlight 3.3). In their identity as partners, adults may choose a relationship with AI over one with a human, casting a toll on mental wellbeing (box 3.4) and family structures. As consumers, they may struggle with automated systems or face identity theft or financial fraud facilitated by AI.[60] And as parents, their digital behaviour shapes future generations. The key here is that in all their identities people need to have choices to be able to act on their beliefs and values (agency) to fully realize their potential.

Keep in mind that many adults still lack access to the internet. While some AI-powered apps can be used without internet access, the most common ones that are accessible in a massified way, such as AI-powered chatbots, require stable broadband connections—an option that many poor people with low levels of education lack (figure 3.6).

Figure 3.6 Multidimensionally poor people with little education lack access to the internet

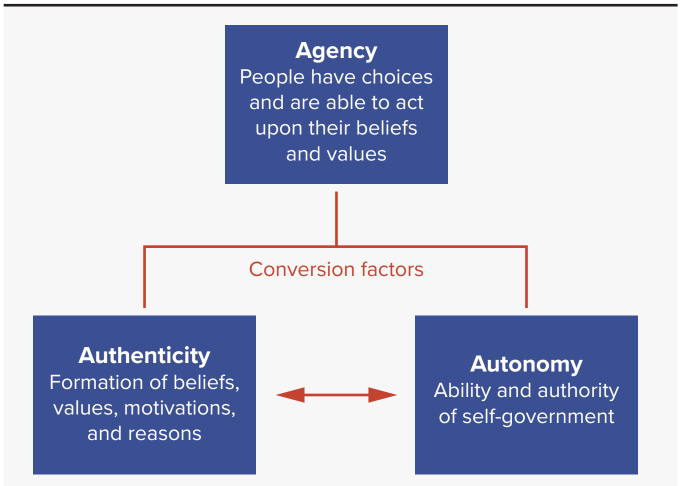


Note: To distinguish between nonpoor and poor individuals, each person is assigned a deprivation score based on their household's lack of access to 10 key indicators of the global Multidimensional Poverty Index. These scores are then summed to calculate the household's overall deprivation score. If the score is 1/3 or higher, the household and everyone in it are considered multidimensionally poor. Individuals with higher levels of education are those who live in a household where at least one member who is of school entrance age plus six years or older has completed at least six years of schooling; individuals with lower levels of education are those who live in a household where no member who is of school entrance age plus six years or older has completed at least six years of schooling. The data are from household surveys (Demographic and Health Surveys and Multiple Indicator Cluster Surveys) that cover nearly 8.1 million individuals in 94 countries.
Source: Human Development Report Office using data from UNDP (2024).

Agency under attack?

A necessary condition for human development is that people can make choices aligned with their values and beliefs and can act on them, a principle summarized in the concept of agency. When beliefs and values are formed more or less independently, they are authentic to that person (authenticity).[61] If that person has the capacity and the authority for self-government, we can speak of autonomy.[62] And if that person is then able to execute their autonomy and act on their beliefs and values, we can speak of agency (figure 3.7). Just as individual conversion factors determine how resources are transformed into capabilities and functionings,[63] conversion factors also shape how authenticity and autonomy are translated into agency.[64] Agency is key to human dignity—and essential for public reasoning.

Figure 3.7 Disentangling autonomy, authenticity and agency in the digital space



Source: Human Development Report Office.

Even in the real world, beliefs and values are not entirely independent but a result of individual and public reasoning, socialization and adaptive preferences, among others.[65] How much authenticity, autonomy and agency does the digital space allow for? Are we not more easily steerable now that we are constantly connected and available for suggestions about what to believe, like or deem important? The digital space adds a layer of complexity to the analysis of this critical aspect of human development (see the discussion of agenticity in chapter 2).

Recommender systems in digital platforms use individuals' online actions to fuel recommendations that guide people to content or products. When these AI algorithms are optimized for engagement, they tailor marketing efforts to encourage people to purchase particular products or stay on the platform.[66] These systems are taking greater control over several areas of life.[67] Through suggestions on whom to follow on X, date on Tinder or work with on LinkedIn and on what book to read, movie to watch or music to listen to, AI influences the culture, work, information and people we are exposed to.[68] As AI is currently implemented, its influence on human authenticity is compounded by the dearth of explainability of AI-generated decisionmaking and content.[69] Some even expect that cultural evolution will be shaped by machines—that is, by a small set of large firms with the same cultural background—given their power to influence social networks, information flows and cultural consumption.[70]

In the case of large language models, there is evidence that the data used in pretraining and the finetuning that happens afterward lead the models to behave culturally in ways that mimic the models' places of origin.[71] And what happens if these platforms are instrumentalized for geopolitical interests,[72] affecting millions of individuals' income opportunities and wellbeing?

Some technology firms intentionally design apps to create a sense of control over the scrolling experience by ensuring that interactive elements remain familiar and predictable.[73] Although this illusionary agency is meant to increase user satisfaction, one of its side effects is that it facilitates masked manipulation. For instance, it makes it easier for certain political groups to diffuse extremist viewpoints, which can undermine democratic processes. And even though some ethical principles may be applied in some countries or regions—as with the Ethics Guidelines for Trustworthy AI from the European Commission[74] or the declaration on the manipulative capabilities of algorithmic processes of the European Council[75]—the blurry lines between persuasion and manipulation make it difficult to distinguish one from the other.[76] At the same time there is evidence that some of these regulations shape the behaviour of the firms behind these digital platforms globally.[77] Still, authenticity and autonomy are threatened and often curtailed in the digital space under the current configuration of AI algorithms, particularly recommender systems (chapter 5). And they are considered subordinates of agency, endangering one of the key aspects of human development in an environment that for many adults takes up a large part of their day-to-day life.

Exclusion, discrimination and frustration through AI-powered systems

AI is increasingly used for customer service, seemingly for human convenience but often to automate tasks previously done by humans in large enterprises. "So-so AI"[78] does not outperform humans, but driven by either hype or cost-cutting pressures, it results in job destruction with no gains in productivity.[79] Social interaction is at the core of these jobs, with social skills and relationships important for problem solving.[80] While customers appreciate the efficiency and round-the-clock availability of AI-powered customer service chatbots,

Box 3.4 Harmful friends without benefits

More and more people have established emotional relationships with artificial intelligence (AI)–powered characters. These characters are constructed to validate users without disagreement, providing emotional and intimate support within seconds.[1] Users perceive the characters—which are really sophisticated chatbots as friendly and accepting peers who are constantly available to provide validation, praise and companionship.[2] The result may be an attachment to an artificial nonempathetic agent whose reactions mostly reflect the user's emotions but are out of the user's control.[3] Since unsatisfied social needs are often the underlying motive for engaging with AI-powered characters, socially vulnerable people are more likely to use these products, which hinder personal growth and can lead to vicious cycles of deteriorating social isolation and poor mental wellbeing.[4]

AI-powered characters are used not only as friends but also as romantic partners in video games (some downloaded more than 10 million times and others with more than 660 million users).[5] These games can produce unrealistic expectations about relationships with a flawless partner and may lead to the rejection of imperfect human relationships.[6]

As people invest considerable time and energy into their seemingly perfect relationships with AI-powered characters, imperfect human relationships can be neglected or even rejected.[7] Some 25 percent of people who regularly interact with these characters report less interest in forming human relationships.[8] This not only erodes people's ability to nurture relationships but also leads to feelings of detachment and alienation from the human community[9] —with 18 percent of frequent users of these features reporting increased loneliness and isolation, even though they perceive a sense of companionship.[10]

Since apps with AI-powered characters tend to come and go from the market, and electricity or devices may not always be available, it is alarming that users report that their mental wellbeing would suffer if certain apps were to disappear.[11] Experts also see potential for addiction;[12] indeed, 32 percent of frequent users show symptoms consistent with behavioural addiction.[13] The biggest contributor to addiction is the experience of conversational flow and attachment, which is generated by AI's perceived intelligence, interactivity, personalization and human-like responses.[14]

There has already been at least one reported teenage suicide related to a synthetic relationship. The AI-powered character indirectly supported the idea of pulling the trigger of the gun.[15] This sad example highlights the danger of emotional bubbles—the false impression that personal emotions are externally validated—which is one of the core differences from relationships among humans.[16] It also illustrates the alignment problem explained in chapter 2. Programs and apps need regulation that protects users from false expectations, such as repeated warnings and reminders that users are interacting with a nonhuman entity. Age restrictions should apply, given the increased vulnerability of younger people.[17]

Notes

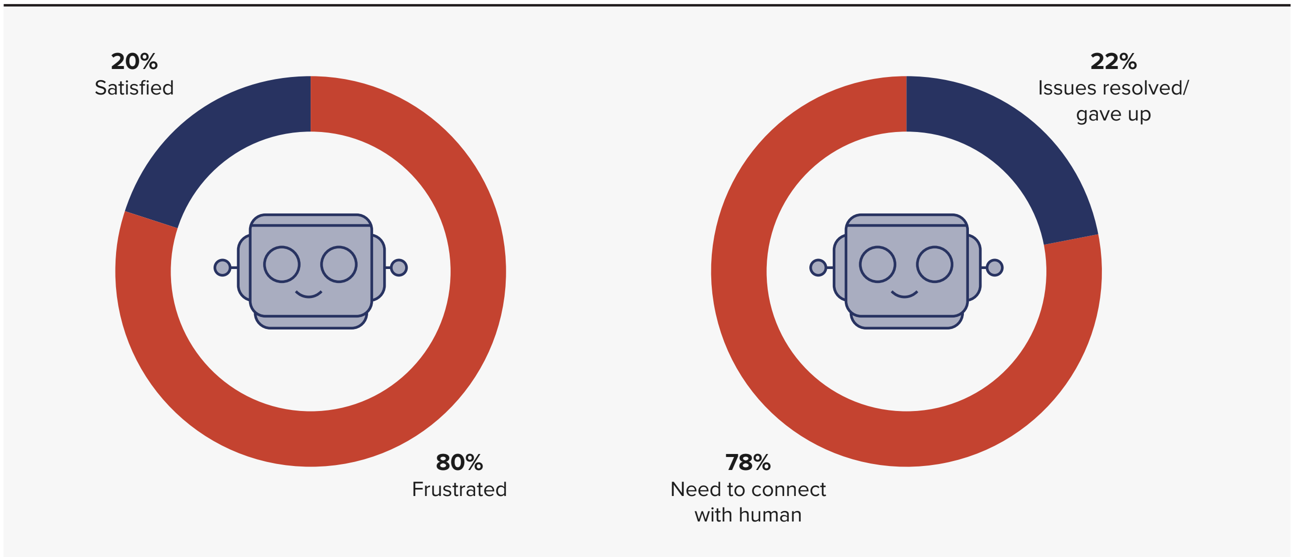
1. Skjuve and others 2021. **2.** Maples and others 2024; Marriott and Pitardi 2024. **3.** Mlonyeni 2024; Zimmerman, Janhonen and Beer 2023. **4.** Mlonyeni 2024; Pentina and others 2023. **5.** Lu-Hai Liang 2019; Xu 2021; Zhou and others 2020. **6.** Forbes 2024. **7.** Zimmerman, Janhonen and Beer 2023. **8.** Forbes 2024. **9.** Boine 2023. **10.** Lafortune, Dubé and Lapointe 2024; Li and Zhang 2024. **11.** Marriott and Pitardi 2024; Skjuve and others 2021. **12.** Xie and Pentina 2022. **13.** Forbes 2024. **14.** Zhou and Zhang 2024. **15.** *New York Times* 2024. **16.** Mlonyeni 2024. **17.** Most users of relationship apps such as Replika are adults (Altchek 2024).

they find the perceived inability to manage complex requests and the obligation to interact with a virtual agent when undesired to be substantial drawbacks.[81] Survey data suggest that 80 percent of customers have been frustrated after interacting with a chatbot instead of a human agent and that chatbots resolved only 22 percent of customers' issues (figure 3.8). All others had to connect with a human agent later.[82] Once a human is brought into the loop after a long series of menus, customers are likely to release their frustration on the representative and provide less information, hindering resolution.[83] Throughout the whole process company–customer relations suffer, which often results in a less positive evaluation of the company.

So, while at first sight, AI reduces costs, it can ultimately damage a company's reputation. The outlook does not seem promising: in 2024, 85 percent of call centre managers in the United Kingdom and the United States that did not already have an automated system planned to implement one.[84] This will also have profound consequences for many middle-income countries that rely on call centres for employment opportunities.[85] In contrast, using AI to support and augment what customer service agents do, as opposed to replacing them, can enhance customer satisfaction (chapter 1).

But digitalization and AI also affect customers in other areas of their daily lives: restaurants where

Figure 3.8 Automated systems may cut costs but distress customers



Source: Human Development Report Office using data from Forbes (2022).

patrons must order using their phone to scan a QR code rather than through a server, travel reservations booked and checked in for online and self-checkouts in grocery stores.

Even when these systems are convenient for some average-age healthy people, they can be a considerable obstacle for others, including illiterate, visually impaired or mentally disabled people, people with passport restrictions, people of colour (when using facial recognition technology), mothers or fathers with small children, and people who lack digital skills. For instance, despite advances in online booking systems, 53 percent of travellers from the European Union, India and the United States reported needing assistance with some or all parts of the booking process.[86] Moreover, people living with disabilities may face difficulties with online check-in and seat selection, as well as inaccessible check-in machines and digital information screens. Screens sometimes lack features such as text-to-speech or adjustable height for wheelchair users. And advanced imaging technology with automated target recognition systems shows a higher false alarm rate for Black people (particularly women), people of East Asian descent, women, older adults, overweight and obese passengers, and passengers wearing turbans or wigs.[87]

The question here is who benefits from the use of digital technology. Right now, substantial service tasks are passed on to customers—without reducing prices and at the cost of discriminating against certain groups. Companies cut labour costs without increasing value for customers, decreasing prices or improving general welfare.

More detailed attention to customer satisfaction is needed, so that digitalization and AI can truly benefit companies and customers alike. Using AI to augment rather than replace people when opportunities for complementarity exist would be a more productive way of deploying AI (chapters 1, 2 and 6). Public-private partnerships could help develop inclusive solutions that offer opportunities for AI augmentation, without longer lines or wait times when choosing to interact with a human.

Caregivers shape the digital generation amid fragmented institutions

Some parents and caregivers consciously teach their children the responsible use of digital technologies. But even those who do not are role models for their children, unintendedly passing on usage patterns, emotional reactions to consumed content and appropriate interaction with nonhuman actors.[88] The current adult generation is thus shaping a whole new symbiotic interplay between humans and machines.

In some countries caregivers lack the skills and experience to teach children the responsible use of digital technology, in part because they have not had access to it or because digital technologies, particularly AI, are changing rapidly. In six African countries 40 percent of children have never received any advice or guidance from caregivers on how to safely use the internet. That is partly because their caregivers do not use the internet, as in Ethiopia, where usage among caregivers is as low as 18 percent.[89]

In other regions of the world, children must compete with technology for their parents' or caregivers' attention. Parents who are using their phone are five times less likely than those who are not to respond to their children's request for attention. And when parents respond while using their phone, reactions are delayed, less affectionate and less focused on the children's needs.[90]

This is where institutions come into play again. During the adult stage of life, the institutional grasp on people is not as direct as during school age, with adults embedded in several institutions, sometimes at the same time. Employees are part of their company. Parents may be involved in their children's schools. People who actively participate in their community may frequently visit community spaces such as public libraries. So, government campaigns, community places, parent associations and workplaces need to transmit sufficient knowledge and awareness that people can make informed choices aligned with their beliefs and values. Only if people maintain a degree of autonomy and authenticity can they exercise their agency.

Older age—trained, empowered and healthier?

The global population is rapidly ageing, with about 1.4 billion people ages 60 and older expected by 2030.[91] As medical care improves and life expectancies increase, more people than ever before are elderly. At the same time digital technology is rapidly advancing, with new digital devices, software and services created every day. This combination of ageing population and rapid innovations in digitalization, including AI, poses some challenges but also opportunities. Few older people are using advanced digital technologies yet, mostly because they either lack access or are unfamiliar and insecure with them, sometimes fearing fraud. But older people who do use them appear less susceptible to drawbacks such as social comparison or addictive features, since their cognitive and brain development has already concluded. So, they can more fully enjoy the benefits of digital technologies, including enhanced social interaction with distant friends and family and features such as telehealth.

Older people need training, access and options

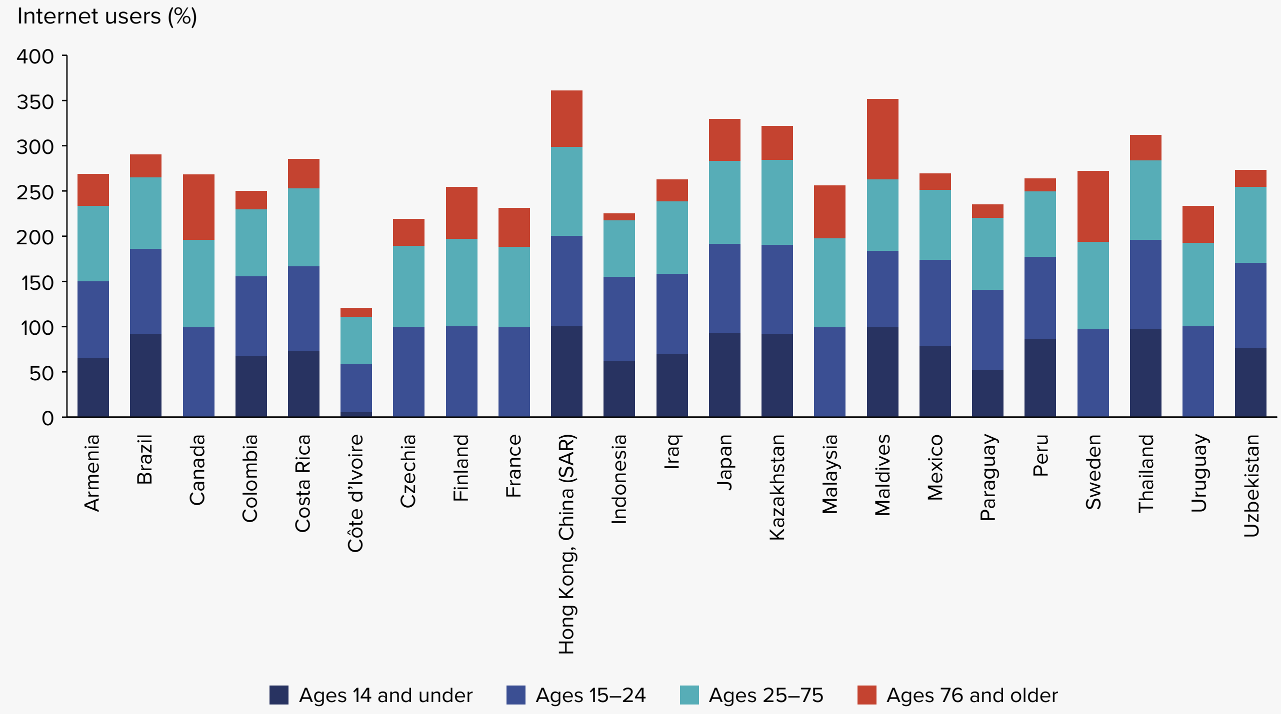
One of the biggest challenges is that many older adults are largely unfamiliar with the newest AI technologies. Fewer than half of people ages 60 and older have used AI-powered tools such as ChatGPT, Google Gemini or Microsoft Copilot.[92] The proportion of older people who are internet users is lower than the proportion of all other age groups (figure 3.9). In Canada 99 percent of people ages 15–24 are internet users, compared with 72 percent of people ages 75 and older. In Côte d'Ivoire, France, Japan and Mexico over 95 percent of young people use the internet, compared with around 50 percent of people ages 75 and older.

The frailer older people become, the less they use the internet and related products and services.[93] Declining cognitive functioning is strongly related to less internet use. Self-perception is also key here: when older people feel more competent, they use the internet more frequently, particularly for banking, shopping, searching for information and contacting friends, acquaintances and relatives.[94]

To the contrary, when older people perceive that learning new skills at an advanced age is counterproductive, self-doubt and anxiety are generated, impeding them from taking on training or venturing into new technologies.[95] And since most older people spend their time outside formal economic or political institutions, it is more difficult to transmit skills and knowledge through trainings at a large scale.

Many digital natives (younger people born in countries with ample access to digital technologies) have not only the relevant skills but also different attitudes, characterized by more trust, less concern and more hopefulness than older people.[96] Fewer than half of older people think that AI-powered products and services have more benefits than drawbacks, compared with more than 60 percent of younger people.[97] And more than 80 percent of older people are concerned

Figure 3.9 **Very little internet use among older people**



Note: Data on internet use among individuals younger than age 15 are unavailable for Canada, Czechia, Finland, France, Malaysia, Sweden and Uruguay. The maximum value of 400 reflects the figure's structure as a stacked bar graph. Each bar includes four segments reflecting the percentage values for four age categories in each country. Because each age group contributes a maximum of 100 percent, the total for any given country cannot exceed 400.
Source: Human Development Report Office using data from ITU (2024a).

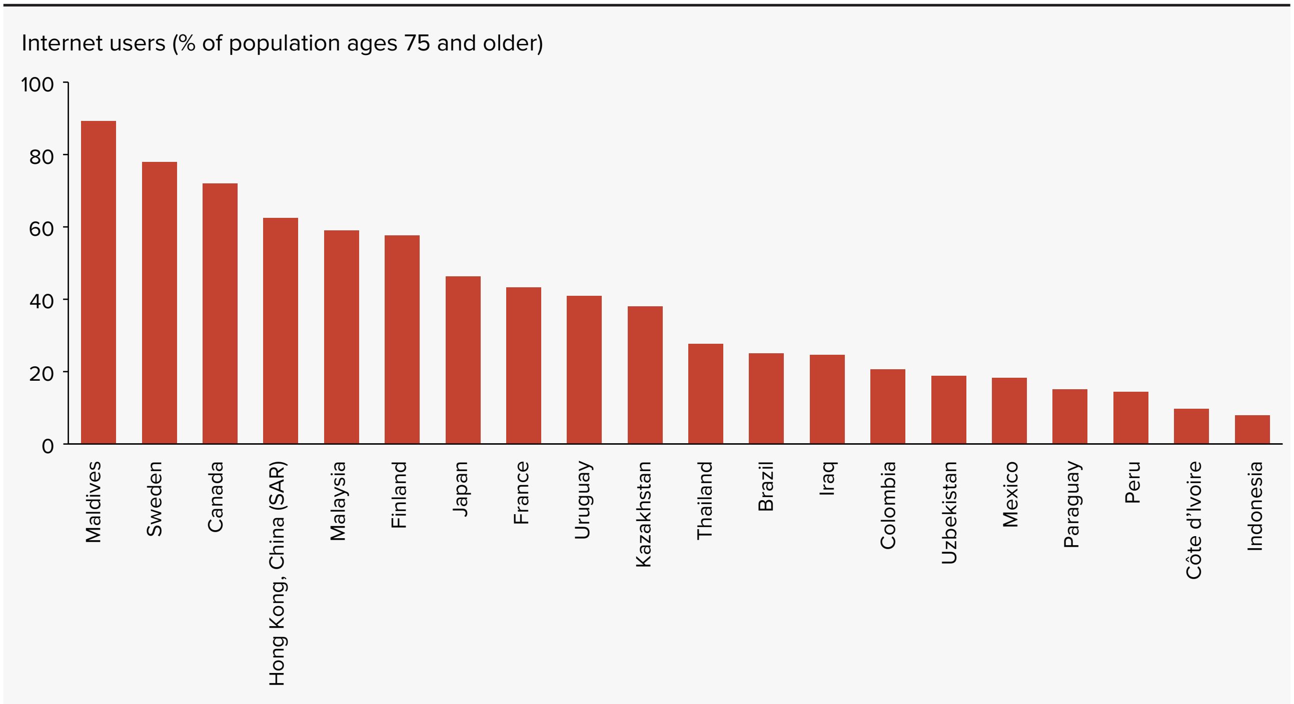
that AI can figure out people's thoughts and make decisions for them.[98] As a result, younger people are much more inclined to use what digital technology has to offer, as reflected in the use gap.

Even so, there is considerable variation in internet use among older adults across countries at different HDI levels (figure 3.10). Older people in low, medium and high HDI countries use the internet less than older people in very high HDI countries,[99] limiting their ability to benefit from a wide range of internet-based services, such as telehealth, social media platforms and online shopping, that could enhance their independence and social engagement.

The Covid-19 pandemic highlighted the double burden of digital and social exclusion that many older people faced during lockdowns. Older people who lacked access to digital technologies or the skills to use them were effectively cut off from some essential services such as telehealth and online shopping, and they faced greater risk of social isolation.[100] Paradoxically, digital technologies can enhance social inclusion among older people. For instance, older people with limited physical mobility can leverage digital tools to sustain their social networks and connections, benefiting their overall wellbeing. They increasingly use video calls, social media and web-based communities to stay connected with family and friends near and far. They are most likely to do so when their partners, friends and family help get them started or updated. This in turn can strengthen bonds across generations.[101]

Older people can seem more vulnerable to online fraud, and data shows they are worried about it.[102] But some studies show that they are actually less likely than younger people to fall victim to it, which might simply be because older people spend less time online.[103] When they do fall victim, they are more likely to experience financial loss, which can be repetitive.[104] When telephone fraud such as phishing and spoofing is included, older people are the most affected, with more than double the total financial loss of other age groups.[105] Reported fraud increased by 14 percent from 2023 to 2024, possibly due to new generative AI-powered tools that use voice cloning in scam calls.[106]

Figure 3.10 Stark variance in internet use among older people across countries with different Human Development Index levels



Source: Human Development Report Office using data from ITU (2024a).

But overall, younger people are more susceptible to the harmful psychological aspects of digital technologies, reporting more feelings of distress, while older people appear to have matured enough to be less affected by them (figure 3.11).

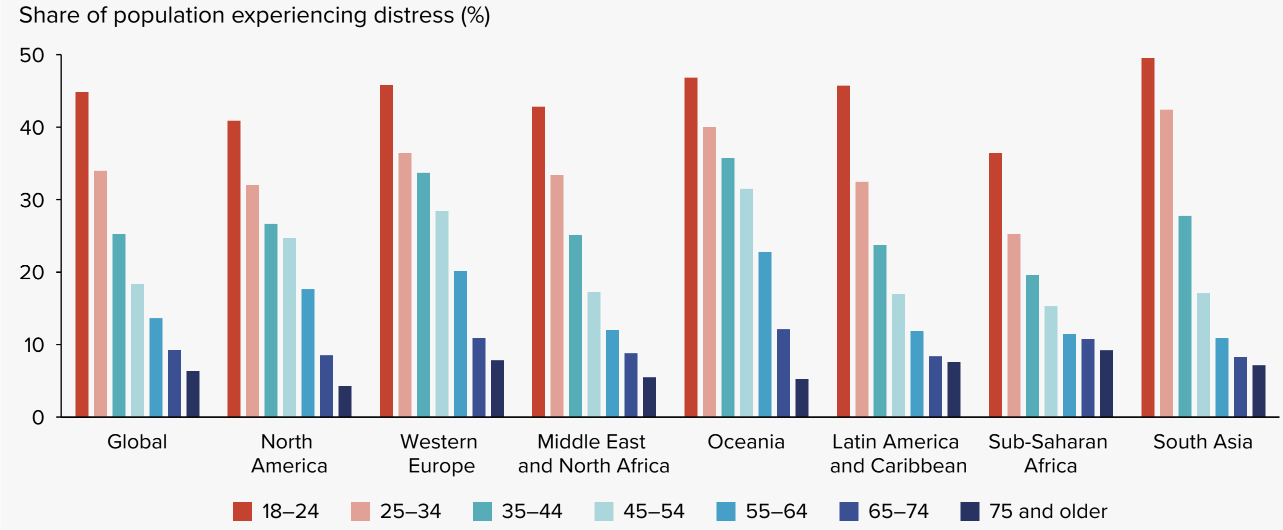
Adults in the older age group tend to have high purchasing power. Older people in the United States could spend an estimated $26.8 trillion on digital technology by 2050.[107] But many apps and devices overlook the physical and cognitive challenges older people face. Product development should ensure options tailored to their needs and abilities. Public-private partnerships can help align people's needs with companies' quests for technological progress, growth and profit. Because many older people prefer targeted training before using new digital technologies,[108] companies should offer human support options.

Bias and promise for older people's health

Fascinating innovations are under way to augment human services in the health sector. AI can help detect subtle patterns in medical images and videos. It can also analyse patterns and meanings in speech or text, recognize disease associations and identify targets for repurposing drugs. These developments improve the early and accurate detection of complex and life-threatening conditions and facilitate timely interventions. Key opportunity areas include:

- AI-powered wearables and signal processing devices can enhance real-time diagnostics and anomaly detection, making it easier to identify health issues early.[109] During the Covid-19 pandemic, telehealth services surged in many parts of the world, and were especially attractive for older people in the United States, where more than 40 percent engaged in video consultations with healthcare providers.[110] The trend has lasted, still generating political debate about insurance coverage several years later[111] and the promise of expanding access to healthcare, as telehealth facilitates services for people with limited mobility, including in rural and remote areas.
- Many older adults require comprehensive health and social care services[112] but frequently receive fragmented care.[113] Coordination between health and social care can be improved by integrating data

Figure 3.11 Across world regions older people who use the internet are less distressed than younger ones



Note: Sample sizes vary by region (between 2,000 and 50,000 internet users). Distress is measured by a mental health indicator that captures 47 items based on a comprehensive coding of mental health symptoms assessed across 126 mental health questionnaires (including the Patient Health Questionnaire-9) and interviews, spanning 10 mental health disorders, as well as items derived from the Research Domain Criteria initiative of the US National Institute of Mental Health. Each item is rated by respondents using a Likert scale with nine options that reflect the item's impact on their ability to function. The ratings are aggregated into the Mental Health Quotient score, which positions individuals in one of six categories from distressed to thriving.
Source: Human Development Report Office using data from Thiagarajan, Newson and Swaminathan (2025).

across health records, ensuring more coherent care. Since disease burdens, functional abilities, care needs and priorities vary widely among individuals, AI can help establish profiles of health needs and predict specific interventions in close coordination with medical staff.[114] But privacy must be protected.

- Preventive care and early disease detection can be augmented through AI-powered technology. AI-assisted radiologists interpret chest X-rays for tuberculosis, mammograms to detect breast cancer and nodules in lung cancer patients in countries as diverse as India, Japan and the United States.[115] AI-powered systems have increased breast cancer detection by 29 percent (with a false-positive rate similar to standard double reading), reducing the screen-reading workload by 44 percent.[116] AI is also used for early stroke prediction and for analysing patients' acoustic and facial expressions to detect Parkinson's disease.[117] Any abnormal movement of a patient triggers an alert and eventually helps humans make a diagnosis.[118]

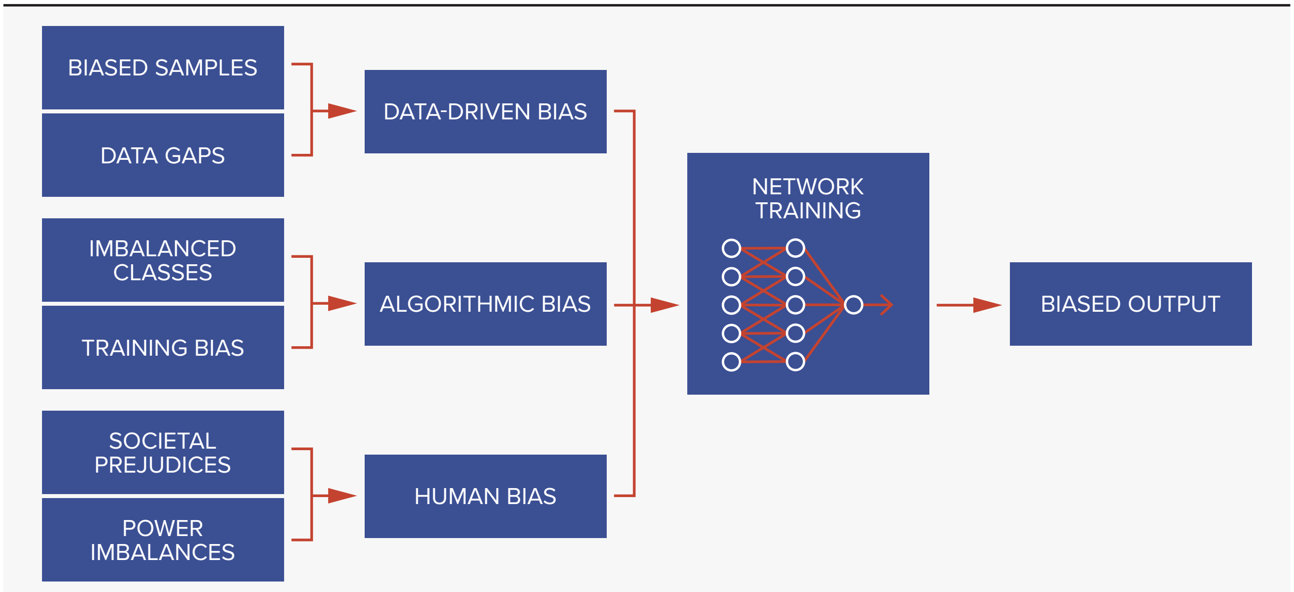
But the use of AI in the health sector is not free of problems. Older people use the healthcare system more frequently than people in younger age groups[119] but are often underrepresented in the datasets that train AI models. Only about 26 percent of AI models include age-specific data, and even those that do contain little information on individuals ages 85 and older.[120] Biases—particularly in representation and evaluation—are introduced at several stages, most frequently in the data-to-algorithm phase and the algorithm-to-user phase.[121]

Underrepresentation, together with social or human bias and discrimination in algorithms, can disadvantage older adults in healthcare access, treatment and outcomes (figure 3.12).[122] Including older adults and their specific needs in developing and training AI models for the health sector is essential for improving services and making them work for people of all ages.

Multistakeholder action for people-centred AI

As AI continues to reshape daily lives, our interactions with it grow increasingly complex. The life-stage perspective helps disentangle risks from benefits and challenges from opportunities, identifying areas for action by multiple stakeholders in society. Since AI is penetrating virtually all areas of people's lives (and

Figure 3.12 **Social, algorithmic and data-driven biases in older people's healthcare**



Source: Norori and others 2021.

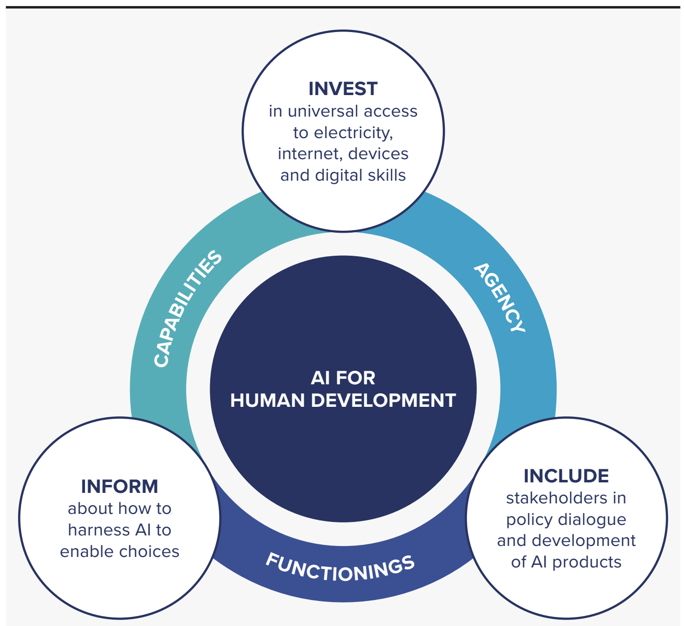
spreading around the world), governments alone cannot make AI work for human development. Collaboration among economic, political and social institutions will help develop and manage AI-powered products and services in ways that expand capabilities and enhance human development. Governments can serve an umbrella function, orchestrating different actors.

Three pillars of the human development framework—capabilities, functionings and agency—can connect AI with a people-centred approach to development (figure 3.13). Following that framework, AI should help people expand their capabilities (what they can do), develop the functionings they have reason to value (what they can be or become) and exercise their agency (being able to act on their beliefs and values).

Investing in universal access to electricity, internet, devices[123] and digital skills can endow individuals with technological resources (for most AI applications) and the skills to use them, expanding their capabilities. Informing people about how to harness AI to develop the functionings they have reason to value will allow them to make educated choices about when and how to use it. Including people of all ages, genders, ethnicities and backgrounds in designing and developing AI products will reflect their diverse beliefs and values, allowing them to exercise their agency. And firms need to be included in policy dialogues on how to make AI work for people.

Urging all stakeholders to double down on the three I's (invest, inform, include), connecting AI to the three pillars of human development, will expand human freedoms and enable people to fully realize their potential.

Figure 3.13 **Harnessing artificial intelligence (AI) for human development—invest, inform, include**



Source: Human Development Report Office.

The decline in young people's mental wellbeing in some parts of the world

Human Development Report Office; David G. Blanchflower, *Dartmouth College;* **Alex Bryson,** *University College London;* **Tara Thiagarajan,** *Sapien Labs;* **Jennifer Newson,** *Sapien Labs*

Until recently, one of the well-established empirical regularities in the social sciences was that subjective measures of wellbeing (such as happiness) followed a U-shaped pattern with age: younger and older people reported higher wellbeing than those in middle age (late 40s to early 50s).[1] Conversely, illbeing (such as despair) followed an inverted-U pattern with age. This empirical regularity was reported in more than 600 published papers documenting its presence in about 145 countries at all income levels.[2]

But around the end of the first decade of the 21st century, this empirical regularity started to unravel, according to a variety of metrics in some parts of the world—particularly in very high Human Development Index (HDI) countries.[3] In the United States wellbeing, measured by life satisfaction, now increases continuously with age (top panel of figure S3.1.1), and reported despair is higher among young people (bottom panel of figure S3.1.1).[4]

Another important change is the difference in the rate of deterioration in wellbeing between young women and young men. While young women have historically reported higher despair than young men in the United States and both groups have reported increased despair since around 2010, the rate of increase has been higher for younger women (figure S3.1.2).

Although results depend, in part, on the types of questions and survey methods,[5] the decline in young people's mental wellbeing does not appear to be universal. For example, there is little evidence that the age structure of wellbeing has changed in Africa over the past decade.[6]

Researchers and policymakers are still trying to determine the reasons behind the changes in some countries and the seeming lack thereof in others. The figures below show that where changes in the wellbeing curve have occurred, they parallel greater smartphone use, leading to hypotheses that some of the documented negative effects of excessive social media use could be driving increases in anxiety, depression and loneliness.[7] Intense smartphone use and deteriorating wellbeing among young people could be linked through a range of mechanisms (box S3.1.1), including constant social comparison[8] and cyberbullying.[9] Poor sleep quality, driven by addictive features, can further impair wellbeing, and the shift from in-person to digital interactions seems to have delayed social and emotional development, increasing feelings of isolation.[10] Also under investigation is whether something intrinsic to social media use is harmful or whether harms emanate from the recommender systems in digital platforms optimized for engagement.[11] Other factors might have also contributed to this dramatic change. A better understanding of mental health issues has led to less stigma, more use of mental health services and thus higher reporting rates.[12] Reduced independence and free play have weakened coping skills,[13] while overprotection and the rise of "safetyism" are making young people more vulnerable to distress.[14]

Smartphones came to prominence in many countries around the time that mental wellbeing among young people began to decline.[15] The rise in poor mental health among young people precedes the Covid-19 pandemic by some years, though the pandemic may have exacerbated the trend.[16] Some studies suggest the trend goes all the way back to the late 1990s,[17] whereas other studies emphasize the uptick in mental illbeing from around 2011.[18]

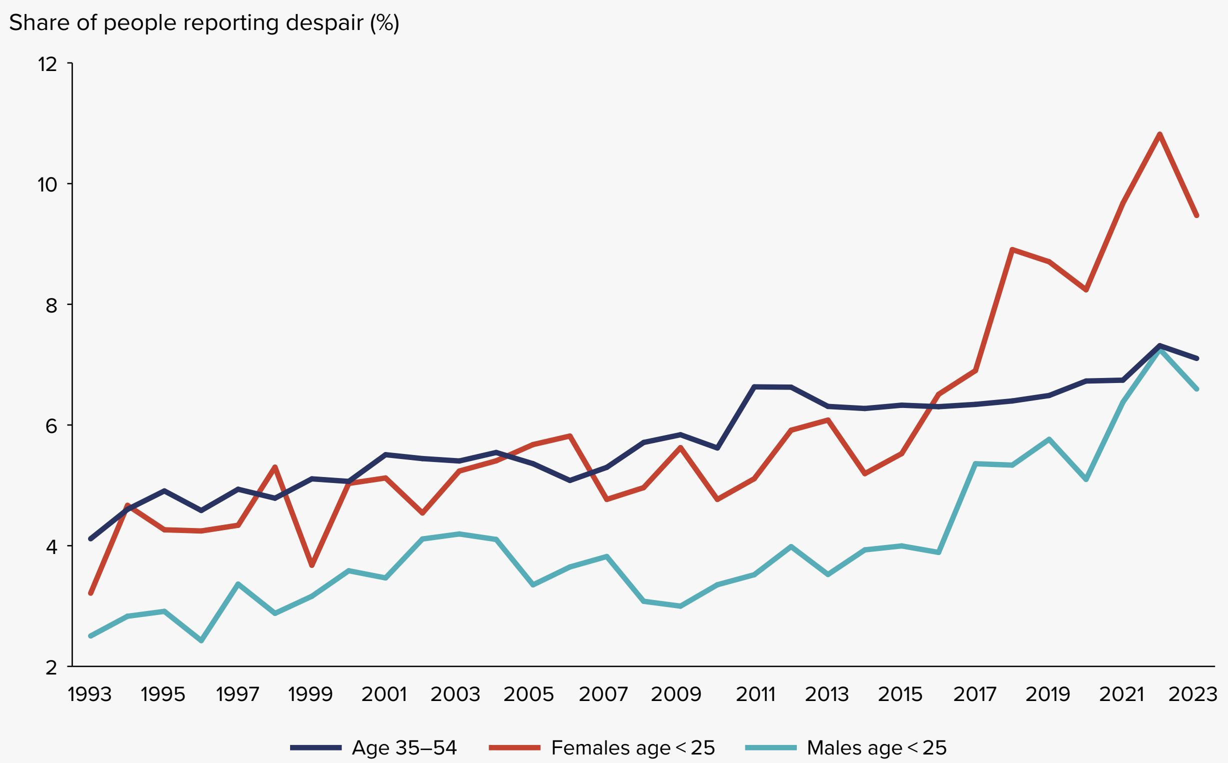
How widespread is this change, and is it really caused by excessive smartphone use?

The shift is not consistent across all datasets or across all dimensions of subjective wellbeing.[19] It is particularly evident in some very high HDI countries[20] and less pronounced or nonexistent in lower HDI countries (with a few exceptions, such as specific surveys in Mexico).[21] This information is telling, considering that most young people in low-income countries are not yet using the internet (see box figure 1 in box 3.3 in the chapter). And detailed case studies

Figure S3.1.1 Declining wellbeing, rising despair among young people in the United States

Note: Mean wellbeing scores are based on responses to the question, "In general, how satisfied are you with your life?" Responses were given on a four-step scale (very dissatisfied = 1, dissatisfied = 2, satisfied = 3 and very satisfied = 4). Share of young people reporting despair is the percentage of young people who responded 30 to the question, "Now thinking about your mental health—which includes stress, depression and problems with emotions—for how many days during the past 30 days was your mental health not good?"
Source: Blanchflower and Bryson (2024c) using data from the US Centers for Disease Control and Prevention's Behavioral Risk Factor Surveillance System.

Figure S3.1.2 Increase in despair in the United States since 2010, especially among women



Source: Blanchflower 2025c.

Box S3.1.1 Connected or disconnected? Exploring possible mechanisms between smartphones and mental wellbeing

Social comparison. Wellbeing is determined not only by what people have but also by how much they think they have relative to others. Well-established in the literature on income and earnings,[1] this extends more broadly to other settings, such as friendship groups and social activity. Smartphones provide regular updates on how others are doing, and young people may perceive their own world as lacking.[2]

Direct impact on brain function. The addictive effect of smartphones is akin to the user returning continually for another “fix,” creating a dopamine response in the brain. Smartphone use can then become an end in itself, with the wellbeing response dependent on more intensive usage. The links between smartphone dependency and mental wellbeing are yet to be fully established, but smartphone addiction could have adverse impacts on behaviours and response mechanisms.[3]

Displacement. The addictive component may cause smartphone use to replace other activities more conducive to mental and physical health, such as maintaining “real” social networks and engaging in social activities outside the home, such as sport and art.[4]

Information overload. Relying on smartphones to perform numerous functions increases screen interaction. For some people, especially young ones,[5] some applications can result in information overload, which can be overwhelming and produce anxiety and stress.[6]

Cyberbullying. The internet extends into a virtual world that is difficult to police. So, smartphone users can be subject to intimidation and bullying, often continually in real time, making it difficult to “hide.” This could have a direct adverse impact on individual wellbeing.[7]

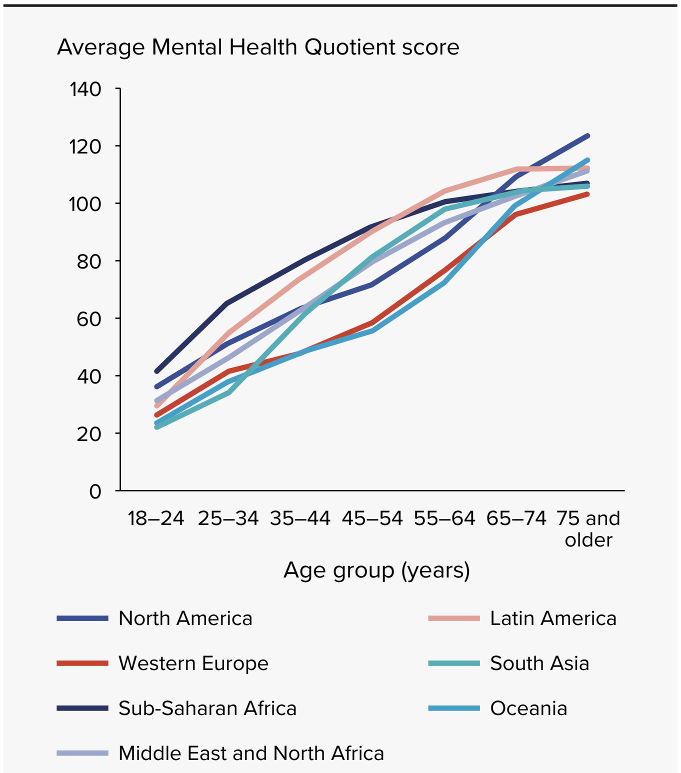
Notes

1. UNDP 2019. **2.** Aubry, Quiamzade and Meier 2024; Braghieri, Levy and Makarin 2022; Faelens and others 2021; Irmer and Schmiedek 2023; McComb, Vanman and Tobin 2023. **3.** Lembke 2021. **4.** Bone and others 2022; Fluharty and others 2023. **5.** Benselin and Ragsdell 2016. **6.** Bawden and Robinson 2020; Matthes and others 2020. **7.** Peebles 2014; Thiagarajan, Newson and Swaminathan 2025; Zhu and others 2021.

have found an association between diffusion of the internet and deterioration in young people's mental wellbeing.[22]

The story becomes even clearer in a global survey that includes only people with internet access. Although the survey samples were not representative of the population, in every country that participated, across all regions, mental wellbeing is lowest for young adults and increases with age (figure S3.1.3). Among the global internet-enabled population, 45 percent of young people ages 18–24 struggle with mental wellbeing at a level that has functional consequences and with symptomatic distress that would be considered of clinical concern.[23]

Figure S3.1.3 Young internet users are struggling everywhere



Note: The MHQ score encompasses 47 aspects of mental function assessed on a life impact scale that spans six dimensions: Adaptability and Resilience, Cognition, Mind-Body Connection, Mood and Outlook, and Social Self. Higher values indicate better perceived mental wellbeing. The survey was conducted during 2020–2024.
Source: Thiagarajan, Newson and Swaminathan (2025) using data from the Global Mind Project at Sapien Labs.

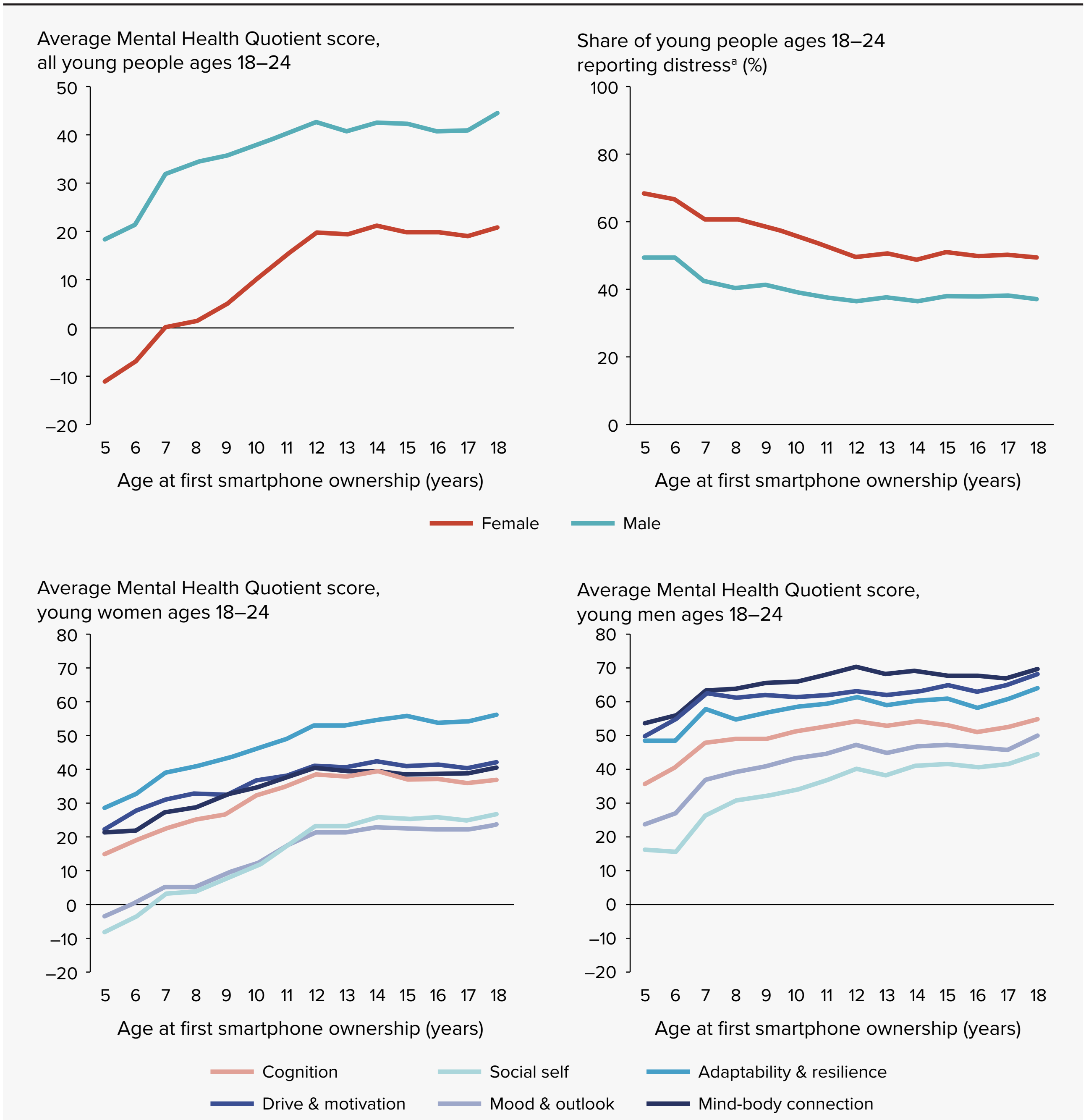
The age at which young people first own a smartphone appears to matter. Among 18- to 24-year-olds today, those who had a smartphone before age 13 show significantly worse mental wellbeing and a higher likelihood of being distressed or struggling than those who received their first smartphone later (top panels in figure S3.1.4). The effects are most pronounced among women and young people who first owned a smartphone at age 5 or 6. Nearly 70 percent of young women and 50 percent of young men responding to the survey now report distress and struggling. By contrast, among those who first owned a smartphone at age 13, the values drop to 51 percent for women and 38 percent for men.

The most affected areas are the social self—a dimension of wellbeing that reflects self-perception and the ability to relate to others—and mood and outlook. The younger the age at first smartphone ownership, the greater the decline in this fundamental aspect of mental wellbeing (bottom panels in figure S3.1.4).

The relationship between age at first smartphone ownership and mental wellbeing is visible in internet-enabled survey respondents across all countries and regions. It appears for both young men and young women but is much stronger for women. Women not only experience a greater drop in wellbeing with younger ages of smartphone ownership but also consistently have lower wellbeing than men overall.

As digital technologies play a larger role in childhood and adolescence and AI-powered applications widen their reach, these findings underscore the need for deeper reflection about the specific mechanisms that cause harm, the risks associated with current AI applications (for instance, recommender systems optimized for engagement based on online behaviour) and the potential for drawing on the new affordances of AI, along with other measures, to mitigate the risks of harm. This agenda, crucial everywhere, is important particularly in countries and settings where digital technologies have not yet diffused as widely, so that societies can be ahead of the curve and harness these technologies to advance human development instead of hindering it.

Figure S3.1.4 The age at first smartphone ownership appears to matter for mental wellbeing



a. Distress is indicated by a Mental Health Quotient score below 0.
Note: The MHQ score encompasses 47 aspects of mental function assessed on a life impact scale that spans six dimensions: Adaptability and Resilience, Cognition, Mind-Body Connection, Mood and Outlook, and Social Self. Higher values indicate better perceived mental wellbeing. The survey was conducted during 2020–2024.
Source: Thiagarajan, Newson and Swaminathan (2025) using data from the Global Mind Project at Sapien Labs.

NOTES

1. Blanchflower 2021.
2. Blanchflower 2025b.
3. Blanchflower, Bryson and Xu 2024.
4. Twenge and Blanchflower 2025.
5. Blanchflower 2025a.
6. Blanchflower and Bryson 2024b.
7. Social media can amplify outrage, status seeking and group conflict but also has the potential to support prosociality and collective action (Van Bavel and others 2024). Its use can have some benefits, such as enabling people to access more targeted content, goods and services that cater to their interests, facilitating access to the labour market by recent college graduates (Armona 2023) and enabling greater opportunities for expression and for creators to disseminate their work (Aridor and others 2024).
8. Aubry, Quiamzade and Meier 2024.
9. Blanchflower and Bryson 2024a.
10. Braghieri, Levy and Makarin 2022; Carter and others 2024; Faelens and others 2021; Huang and others 2023; Irmer and Schmiedek 2023; Khalaf and others 2023; McComb, Vanman and Tobin 2023; Stuart and Scott 2021; Scott, Stuart and Barber 2021, 2022; Twenge and others 2020.
11. Lewandowsky, Robertson and DiResta 2024. The purpose of social media use (to access information, to seek entertainment or to express oneself) also matters (Qiao, Liu and Xu 2024).
12. Corredor-Waldron and Currie 2024.
13. Haidt 2024.
14. Lukianoff and Haidt 2019. Evidence is from the United States.
15. Blanchflower 2025a; Blanchflower and Bryson 2024c; Blanchflower and others 2024.
16. Blanchflower, Bryson and Bell 2024. This seems to be the case for the United Kingdom but not for the United States (Blanchflower, Bryson and Xu 2024).
17. Blanchflower, Bryson and Bell 2024.
18. Blanchflower, Bryson and Xu 2024.
19. Blanchflower and Bryson 2025.
20. Twenge and Blanchflower 2025.
21. Blanchflower and Bryson 2024b, 2024c, 2025.
22. For the case of Italy, see Donati and others (2022).
23. Thiagarajan, Newson and Swaminathan 2025.

The social media trap

Leonardo Bursztyn, *University of Chicago;* **Benjamin Handel,** *University of California, Berkeley;* **Rafael Jimenez Duran,** *Bocconi University;* **Christopher Roth,** *University of Cologne*

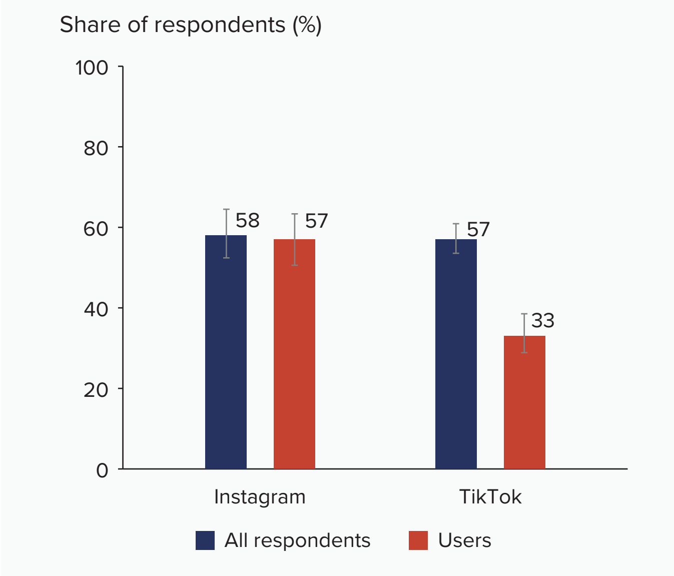
In recent years the mental health crisis among teenagers and young adults has become increasingly concerning. Social media platforms, while serving as tools for connection and communication, have been linked to feelings of anxiety, depression and loneliness among teenagers and young adults.[1] This has sparked a policy debate surrounding the potential regulation, or even outright prohibition, of social media platforms. In May 2023 the US Surgeon General pushed for a better understanding of the possible "harm to the mental health and well-being of children and adolescents" from social media, as well as the impact of stricter limits and standards for use.[2] In late 2024 the government of Australia introduced a general ban on social media for users under age 16.[3]

The policy debate around social media critically hinges on welfare estimates of social media products: what is the value of social media to its users?

Some platforms such as Instagram and TikTok are extremely popular among young people, to the point that it can be very painful to stay off the platforms. Not using them would lead to tremendous fear of missing out and potential exclusion from many social interactions. Could large numbers of young users of these platforms not want to stop using them while also preferring to ban them? In other words, is there a social media trap?[4]

One way to answer this important question is to ask young Instagram and TikTok users if they would prefer to live in a world with or without these platforms. Among a sample of just over 1,000 US college students, over 55 percent of Instagram users and 33 percent of TikTok users would prefer to live in a world where the platform did not exist (figure S3.2.1).

Figure S3.2.1 **Respondents who prefer to live in a world without the platform**



Note: Error bars represent 95 percent confidence intervals.
Source: Bursztyn and others 2023.

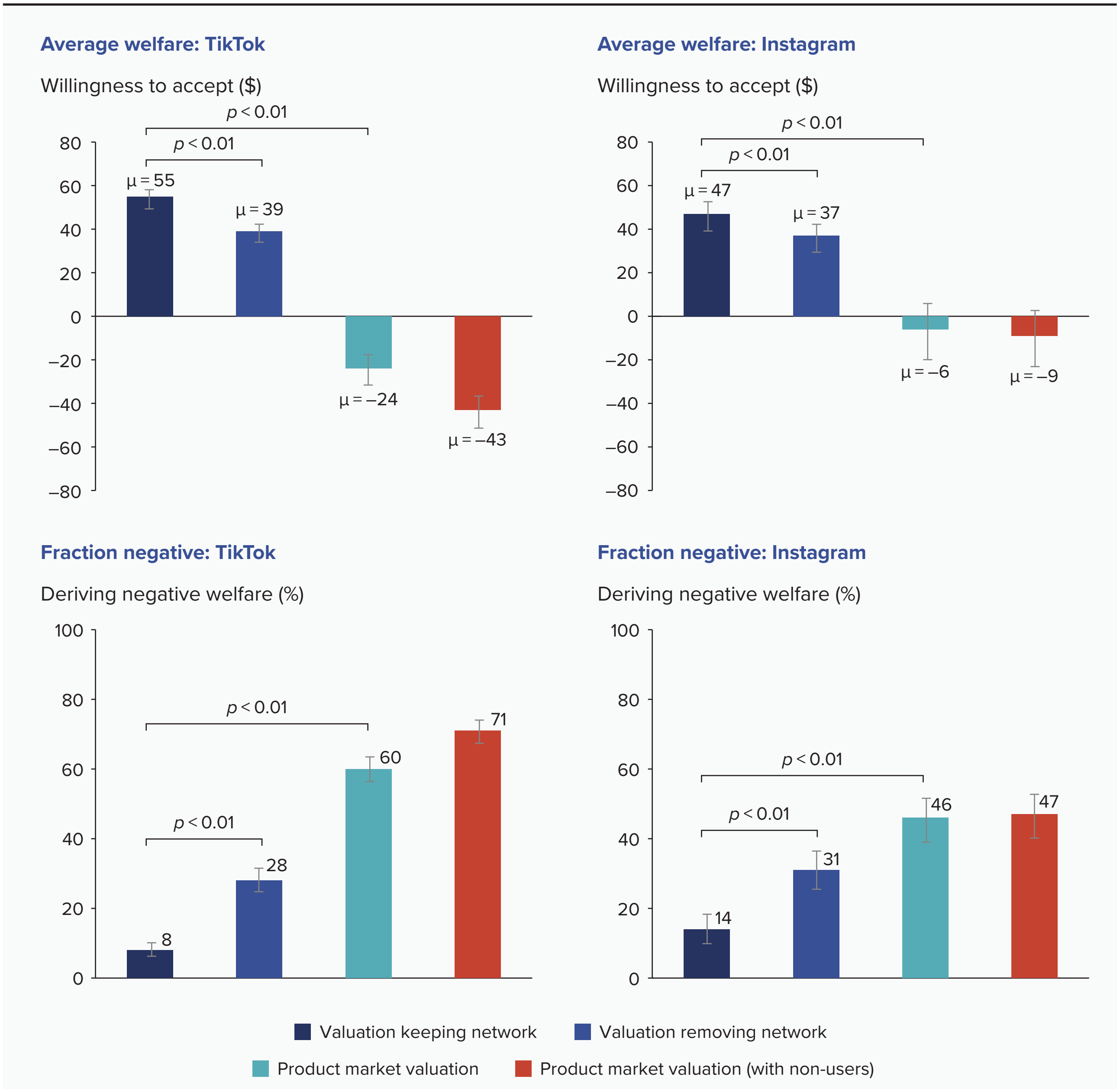
Moving beyond just asking survey questions, an experiment with the same sample of college students uses financial incentives to infer their valuation of four scenarios involving the platforms. The first scenario (called "Valuation keeping network") is deactivating the respondent's account for four weeks, which delivers the standard measure of individual consumer surplus. The remaining scenarios shrink the size of the respondents' social media networks by introducing the possibility of collective deactivation, where all students on campus who are participating in the experiment would also deactivate their accounts. Such collective deactivation would be implemented if the researchers recruited two-thirds of the students at the college for the experiment. The second scenario (called "Valuation removing network") measures individual willingness to deactivate conditional on all other participating students having been asked to do so, in exchange for monetary compensation. The third (called "Product market valuation") measures whether individuals are willing to forgo payment or instead require a payment to deactivate all participating students' accounts.

Students need to be paid around $50 to deactivate Instagram or TikTok for four weeks, if they expect to do it alone (figure S3.2.2). At the same time, 46 percent of active Instagram users and 60 percent of active TikTok users are willing to pay to have their own and others' accounts deactivated for four weeks.[5]

Why does this happen? When participants were asked, the dominant reason they mentioned is exactly what one would expect for a social media trap: fear of missing out.

Such fear can be grounded in reality: nonusers miss out on the social interactions happening on social media and on the offline discussions based on those interactions. As one respondent who continues to use the platform even though they would prefer to live in a world where it didn't exist wrote, "I feel like if I stop using it, I will be completely out of the loop." It may

Figure S3.2.2 Consumer surplus across welfare measures



Note: Error bars represent 95 percent confidence intervals.
Source: Bursztyn and others 2023.

be costly to use the platform, but it is even costlier to be the only one not using it.

Recent academic work points to self-control issues and addiction being major factors in young people's social media use.[6] The above findings on a collective trap indicate that, even in the absence of self-control problems or addiction, many users are joining and staying on social media platforms despite not enjoying them. This conclusion challenges the argument that because people spend a lot of time on social media, it must be creating value for them.

What are the policy implications? Many social media users seem to prefer to live in a world without social media but are willing to quit it only if others also do. This characterizes a coordination problem. One potential policy avenue is regulation and bans—actions policymakers are discussing and implementing. Another avenue is to provide coordination tools that allow users to cut down their social media use together. These could be designed and developed through public-private partnerships or using incentives or subsidies.

NOTES

1. Allcott and others 2020; Allcott, Gentzkow and Song 2022; Braghieri, Levy and Makarin 2022.
2. See, for instance, Richtel, Pearson and Levenson (2023).
3. For popular press coverage on this matter, see, for instance, Ritchie (2024).
4. This is the idea behind Bursztyn and others (2023).
5. Identical experiments run by the authors on the deactivation of navigation apps rule out that the effects are mechanically driven by aspects of the elicitation procedure and help rule out that the findings simply reflect a general distaste for big tech or digital products.
6. Allcott, Gentzkow and Song 2022.

Worker agency in the digital age

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Digital technologies are transforming the workplace. This spotlight is concerned with the effects of digital technologies on worker agency, which broadly refers to workers' effective ability to make choices that align with their beliefs and values, to draw meaning from their work and to exercise adequate control over their work and work environment.[1]

The relationships among digitalization, agency and the workplace are dynamic, with each element shaping and being shaped by the others. Digitalization transforms workplace structures and processes, which has effects on the agency that workers can exercise. In turn, agents shape how digital technologies are implemented, resisted or adapted in workplace settings.[2]

The ability to exercise agency at the workplace is broken down in four key elements: C-A-R-E.[3] Autonomous agency requires a substantial degree of effective control (C) of the circumstances in which one works. It requires meaningful input into the co-creative authorship (A) of the work one carries out. The work process also needs to be socially embedded in valuable relationships (R) connecting one exercising agency to others. Lastly, one's participation in the work process must be informed by an understanding of it that ensures a degree of epistemic agency (E). The four elements of CARE are interrelated and inform one another.

C—control and discretionary authority

Agency in the workplace relies on having a certain amount of discretion about how to carry out tasks—free from meddlesome or punitive surveillance and (technological or human) micromanaging—something that is widely valued across cultures and work environments.[4] Although digital technologies offer numerous opportunities for workers to personalize their tools, the nature and complexity of digital tools and the fast pace of automated processes pose a threat to this discretion in three ways.

First, control requires understanding (see also the subsection below on epistemic agency and understanding). By limiting employees' insight into the technologies with which they work, many work environments make it difficult for workers to assess the adequacy of digital solutions or outputs, something that could be exacerbated by the greater diffusion of artificial intelligence (AI). Consider the proverbial "keeping humans on the loop," expected to ensure that automated systems do not run unchecked.[5] Without sufficient access to information, workers may be unable to confidently make well-informed decisions—reducing their oversight to little more than a formality.

Second, workers' control over their work can be limited by rigid structures imposed by digital solutions, reducing their ability to adjust system settings, correct inaccuracies, override automated decisions or address issues linked to the use of the digital systems. For example, staff at a child welfare agency in Wisconsin reported frustration at losing decisionmaking power to an algorithm for foster care allocation and criticized its shortcomings, such as a lack of understanding of childhood trauma.[6]

Third, even when control is possible in theory, it can be undermined in practice by narrow tolerances in fast-paced processes, by repetitive or complex tasks that can foster automation bias, the tendency to uncritically accept algorithmic outputs. In such cases decisions often default to automated outcomes. For example, in healthcare settings automation bias has been associated with cognitively demanding diagnostic tasks.[7]

A—authorship and ownership

Authorship and ownership of one's professional activities are key for workers to derive meaning, purpose and a sense of accomplishment in the workplace.[8] Authorship ensures that work outcomes align with one's values and intentions, whereas ownership involves a sense of responsibility for one's work and is a prerequisite for feeling recognized and esteemed for one's contributions.[9] Digital technologies can alleviate several tedious tasks, such as bookkeeping or repetitive communication, freeing time for more meaningful or interesting work, but these potential benefits are rarely reaped evenly across occupational categories or sectors.

For example, gaps in work autonomy may widen between white collar workers and shop floor or assembly line workers.[10] AI technologies, if applied in the same way as classical programming, risk extending this to additional categories of professional and white-collar jobs. When pace, timing and order are determined by technology (see also the subsection above on control and discretionary authority), there is little room for authorship, leaving employees feeling fungible. Increased surveillance practices—which can now encompass workers' "thoughts, feelings and physiology, location and movement, task performance, and professional profile and reputation"—further erode ownership.[11] Such technologies coerce workers into becoming ever more efficient, significantly undermining authorship.[12]

R—relationships and community

Agency is intimately linked with being embedded in social relationships.[13] In the workplace, relationships influence employee outcomes such as work attitudes, withdrawal and effectiveness.[14] Digitalization can disrupt traditional forms of communication and community, changing the feasibility and nature of coworker interactions.[15] While remote work offers several advantages on the control dimension, it has been shown to lead to increased feelings of loneliness and isolation.[16] But even for onsite work, digital solutions can reduce formal and informal interactions at the workplace due to isolating working conditions that require more screen time and fewer face-to-face interactions, automated workflows that replace collaboration, asynchronous forms of communication and more comprehensive surveillance systems. These developments undermine worker agency, since sharing and comparing experiences with others play a fundamental role in how we perceive ourselves and our environment and in how we uncover and address injustices.[17]

E—epistemic agency and understanding

Epistemic agency and understanding support many of the other elements of worker agency insofar as they are necessary for seeing one's workplace tasks as justified and, relatedly, for being motivated to carry them out. Insight into the work process and the context of work also provide intrinsic value to the worker and productive activity. Digital solutions, especially ones using machine learning techniques, can hamper understanding because they lack transparency in a variety of ways. The system's workings and capabilities are not disclosed to the employee—for instance, due to negligence or intellectual property restrictions. The employee does not have the technical skills necessary to comprehend how the system functions. Or the system's nonlinear and complex architecture inherently resists human introspection (lack of interpretability).[18] Epistemic agency also involves workers having the opportunity to contribute with their own knowledge and expertise both to their own work processes and to their overall work environment. This includes not only the capacity to question and correct digital solutions where necessary but also the opportunity to shape how such solutions are implemented in their broader work context.

The CARE approach to worker agency suggests two recommendations. First, policymakers can work with the private sector to establish guidelines for algorithmic decisionmaking—and digitalization more broadly—in the workplace. Such guidelines at a minimum need to ensure that automated decisions are explainable and contestable by employees, thereby securing control and epistemic agency. Employer disclosure of the extent of digital monitoring at the workplace would be important. Guidelines on work surveillance should be informed by notions of prerogative to contest automated decisions and take seriously the principle of keeping humans in the loop. Second, worker participation and an ability to unionize can support securing worker agency. This could involve proactively facilitating workers' possibilities to organize and having firm governance structures that allow worker representatives to engage in participatory design and decisionmaking.

Table S3.2.1 The CARE framework

Characteristic	C—control and discretionary authority	A—authorship and ownership	R—relationships and community	E—epistemic agency and understanding
Deficits	→ Lack of understanding → High process speeds → Rigid structures → Impossible to correct system → No point of contact	→ Overly controlled environments → Fungibility → No professional development → Lack of work autonomy → Surveillance	→ Isolated working conditions → Automated workflows → Asynchronous communication → Surveillance → Lack of social embeddedness	→ Lack of information → Lack of expertise → Lack of interpretability → Inability to overwrite outputs
Enablers	→ Discretionary authority → Understanding → System support → Customizability → System flexibility	→ Task customization → Feedback mechanisms → Opportunities for professional growth → Accountability frameworks → Reduced micro-management	→ Social interactions → Collaboration → Community → Open communication channels → Privacy safeguards	→ Transparency of digital systems → Technical literacy → Contributing expertise → Participation in digital solutions
Assessments	→ How much discretion do employees have to decide how and when tasks are performed? → Do employees have sufficient information to make informed choices? → Is there a risk that employees passively accept digital outputs without question? → Do employees have access to adequate support when addressing errors or issues related to digital systems?	→ Do employees feel their work reflects their values and professional goals? → Do tasks align with employees' skills and expertise? Is there room for skill development? → Are there systems of accountability that respect employees' expertise, or do they create fear of overstepping? → Can employees challenge and question the outputs of automated systems without negative repercussions?	→ Do digital solutions replace opportunities for formal and informal exchange? → To what extent do automated workflows replace collaborative processes? → How do digital solutions impact employees' sense of belonging and self-perception at work? → Does digitalization limit employees' ability to share experiences that help uncover and address workplace injustices?	→ Are employees provided with sufficient information and training to understand how digital tools and systems function? → Are decisionmaking processes transparent and accessible to workers? → Are employees encouraged and given the opportunity to contribute their knowledge and expertise to their work processes? → Do employees have a voice in how digital solutions are implemented and integrated into their broader work environment?

Source: Authors' elaboration.

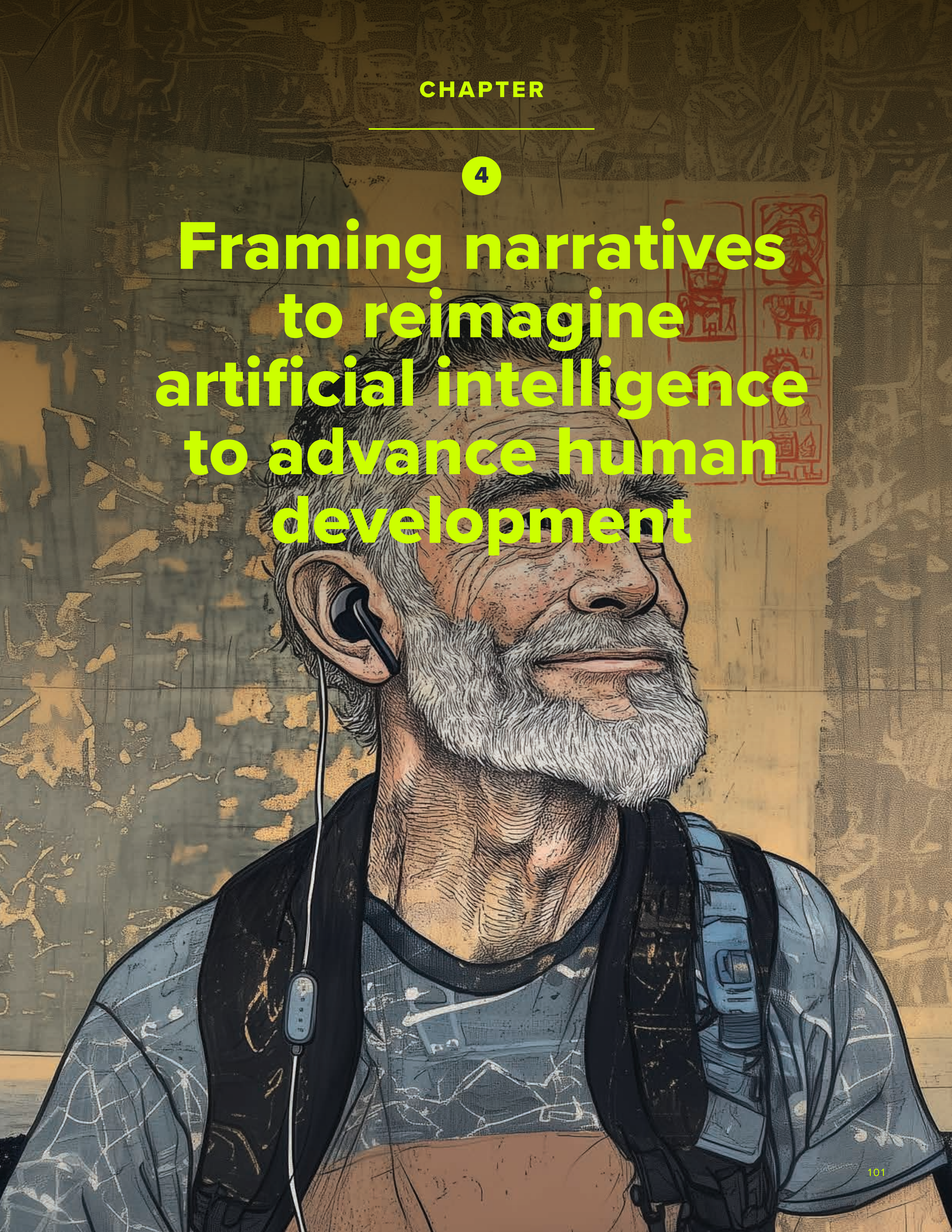
NOTES

1. Eteläpelto and others 2013.
2. Eurofund 2025; Pärli 2022; Unruh and others 2022.
3. Anderson 2013; Mackenzie 2014; Mackenzie and Stoljar 2000.
4. Gagné and Bhave 2010.
5. Leins and Kaspersen 2021.
6. Saxena and Guha 2024.
7. Lyell and Coiera 2017.
8. Aslan and Atesoglu 2021.
9. Anderson 2013.
10. Eurofound 2025.
11. Ball 2021, p. 23.
12. The Guardian 2024; Marsh, Vallejos and Spence 2022.
13. Landes and Settersten 2019; Mackenzie and Stoljar 2000.
14. Chiaburu and Harrison 2008; Pereira and others 2023.
15. Honneth 2024; Lane and others 2024.
16. Gallup 2024.
17. Honneth 2024; Hopster 2024; Milano and Prunkl 2025.
18. Milano and Prunkl 2025; Selbst and Barocas 2018.

CHAPTER

4

Framing narratives to reimagine artificial intelligence to advance human development



Framing narratives to reimagine artificial intelligence to advance human development

As the impact of artificial intelligence (AI) on human development remains uncertain, narratives can play a crucial role in shaping our choices. Rather than a techno-determinist narrative that assumes that AI alone will either solve all our problems or threaten the future of humanity, AI's direction and deployment will be contingent on individual and collective choices. Institutional and social choices can enable AI to expand people's capabilities and agency, as illustrated through AI's applications for people with disabilities, care systems and gender equality, as well as in conceptualizing and mitigating AI bias. To do so, existing benchmarks to evaluate AI's progress and safety should be complemented with ones that assess the impact on advancing human development.

“For AI to be a boon, we must reorient; pushing AI capabilities alone is not enough.”

—Bengio and others 2024, p. 2

Contrary to current narratives that assume a linear link from new technologies to social change, artificial intelligence's (AI) impact on people is rooted in social structures and contingent on people's choices. AI and people are immersed in a reciprocal relationship shaped by social, economic and political processes. This two-way relationship, established time and again in past episodes of technological change, demands attention in order to navigate fast-paced AI innovations in ways that advance human development.

Narratives about technology—both in popular media and in the policy arena—often portray AI as something that can, on its own, catalyse social change. They disproportionately focus on availability and affordances of new technologies as ends in themselves, as illustrated by the way the media, investors and firms report the achievements of AI models on a range of benchmarks.[1] Yet social change is an outcome of complex interactions of technologies with institutions, including social norms. And progress is neither inevitable nor neutral[2]—it depends on our choices: whether we ensure that the benefits of technological advancement are broadly distributed and expand people's freedoms and choices to lead lives they value and have reason to value.

AI affordances do matter. But considering these societal drivers can help with the design, development and use of AI that expands people's agency and avoids creating or reproducing inequalities.

The nature of AI, its implications for society, and its future development and deployment remain uncertain. This makes landing on a set of choices to harness AI's potential much more complicated. So this uncertainty makes narratives much more determinant in shaping our choices, given that there is little else guiding us about what the future will hold (spotlight 4.1). Framing narratives about how AI can advance human development is crucial at a time of momentous changes in policies, institutions and regulations. A narrative centred on advancing human development can inform crucial decisions that will have implications in the years, perhaps decades, to come.

Along with the content of the narrative, the process matters as well. Debates about AI must reflect diverse voices and perspectives and extend beyond the agenda of powerful players because in looking at their interests, we may lose sight of broader social implications. The main argument of this chapter is that the narratives about AI, and the processes around them, should focus not just on what AI can do but also on how it can enhance people's capabilities. Framing narratives this way can support power realignment (chapter 5) and harness the opportunities for AI to advance human development (chapter 6).

Beyond techno-determinism: Technological change shapes and is shaped by society

“Because technology is highly malleable, there is no scarcity of compelling stories that can support alternative paths for technology. There are always many technological choices, with very different consequences, and if we get stuck with a single idea or a narrow vision, it is very often not because we are short of options. Rather, it is because those setting the agenda and commanding social power have imposed it on us. Correcting this situation is partly about changing the narrative: dissecting the driving vision, revealing the costs of the current path, and giving airtime and attention to alternative futures of technology.”

—Acemoğlu and Johnson 2023, p. 97

Narratives about AI often oversimplify technology's impact on social change by assuming that technology alone can shape social outcomes—called techno-determinism. For instance, when digital technology is applied to alleviate certain social problems, there has long been a tendency to assume that, by its mere implementation, it will generate the desired results.[3] AI has been portrayed as a revolutionary technology, with the potential to solve complex problems, unlock economic growth and contribute to human flourishing.[4] But the history of science, technology and innovation points to a more nuanced reality—technology always coevolves with economic, social and political systems[5] and is codetermined with the evolution of norms, institutions and public policies.[6] For example, economic expansion during the Industrial Revolution was the product of new technology along with new ways of organizing economic production, new workforce skills and a range of new institutions that emerged in response to new demands.[7]

A deterministic view of technology drives a dichotomy between utopian and dystopian futures for humanity with the rise of AI, often fuelled by media representations of AI with a great deal of hype and exaggeration.[8] Two dichotomous perspectives—one optimistic, where technology is considered a positive force for progress, and another pessimistic, where technology is inexorably outside human control—have one thing in common: they oversimplify the complex interactions between technology and society and project a sense of inevitability for the social consequences that follow technological change.[9] They seemingly leave little room for human agency to shape technological change in ways that enhance people's freedoms, opportunities and choices.[10] In contrast with this view, this chapter argues that the outcomes of technological change are not inevitable; they are contingent on social choices.[11]

Moreover, technologies are never neutral. They embody social contexts, choices and values.[12] The characteristics of AI deserve attention in their own right. But the impacts cannot be analysed in isolation from the contexts in which AI is deployed. The interactions between technology and society are interdependent and multifaceted, and they both change in relation to each other.[13] The impacts of AI stem not from individual technical components but from the dynamic ways they interact with social forces and from how they are used, by whom and for what purpose.[14] Human agency and context matter.

With the rapid rise in AI's development and availability, techno-deterministic narratives assume that technological solutions will mitigate complex social challenges in such areas as education, healthcare and social services. To be clear, nothing is inherently wrong with intending to deploy new technologies to address societal challenges, as argued in much of this Report. History is replete with examples of technological changes that revolutionized human lives, bringing massive improvements in living standards, connections and economic growth. Indeed, AI can be massively helpful. For example, generative AI in education can help close persistent gaps by paving the way for truly adaptive, on-demand and personalized teaching. It also has the potential to enhance the quality of healthcare by, among other things, reducing administrative burdens on providers (chapter 6).

Even so, AI cannot provide quick fixes—its deployment alone does not determine social outcomes. Such promises of quick fixes often appeal to underfunded institutions.[15] A technology may accomplish a narrowly defined goal, but doing so in a way that solves problems for all rather than for just a subset of individuals who can afford to benefit matters. Ultimately, how technological solutions determine social outcomes is shaped by social and institutional arrangements.

"The impacts of AI stem not from individual technical components but from the dynamic ways they interact with social forces and from how they are used, by whom and for what purpose. Human agency and context matter

But deploying technology as solutions is not the only thing that matters; the way in which technology development occurs also involves choices that could lead to differing outcomes across social groups. Technological change can reinforce, amplify and reconfigure inequalities, potentially exacerbating discrimination or generating new forms of it. Seemingly innocuous design features can mask social choices, with profound consequences.[16] For instance, gender inequalities in technology production and consumption are reflected in the development and use of AI.[17] AI has the potential to ameliorate social inequalities, but achieving this potential—and empowering people and communities—requires considering social contexts so that policy and institutional choices on the trajectory of AI and its deployment advance human development.[18]

Framing a narrative on AI that considers this broader codetermination of technology and society can support the design and use of AI in ways that advance human development. Through the examples of people with disabilities, the care system, women and AI bias, this chapter illustrates how narratives matter and how their framing can help in reimagining choices about technologies, policies and institutions to expand people's capabilities and agency. Narratives not only affect the kind of technologies we decide to develop or use—they also shape how we define problems in need of technological solutions.

"Through the examples of people with disabilities, the care system, women and AI bias, this chapter illustrates how narratives matter and how their framing can help in reimagining choices about technologies, policies and institutions to expand people's capabilities and agency. Narratives not only affect the kind of technologies we decide to develop or use—they also shape how we define problems in need of technological solutions

AI's potential for people with disabilities: Framing a more nuanced narrative to expand human development

People with disabilities provide a compelling illustration of the substantial opportunities and challenges that AI presents. Technological innovations can play a major role in facilitating choices and open opportunities for people with disabilities. But AI's potential to revolutionize the lives of people with disabilities would have to go beyond framings of technologies as enablers to overcome impairments. Indeed, relying on various technologies for fundamental life functions exposes people with disabilities to disproportionate social marginalization when the technology is inaccessible, inappropriate, inconsiderate of their needs and preferences or incongruous with their identities. While AI tools create enormous possibilities for people with disabilities, they are insufficient to promote inclusion and participation on their own. Inclusion is a fundamentally social process that entails broader changes in social norms, institutions and policies.

For people with disabilities, human–machine interactions and machine-mediated human–human interactions are hardly new.[19] People with disabilities have long relied on various kinds of technologies for everyday functions, such as communication, mobility, writing and reading. In fact, many technological developments—such as email, text messaging, optical character recognition, text to speech, speech to text and smart home systems—were originally designed for people with disabilities before being more widely adopted.[20] These technologies generally fall under the umbrella of assistive technologies.[21]

Over the years digital technologies have brought about considerable advancement in assistive technologies, offering new opportunities to enhance independence, participation and access.[22] For example, mobile phones function as a cost-effective assistive technology.[23] Because of their versatility, they can include multiple accessibility features—such as the ability to access information in different formats—into a single device. This is emblematic of a broader shift where inclusive features are integrated into mainstream consumer technologies, reducing the need for specialized products for specific needs.[24]

The recent advent and massive adoption of AI have enabled pathbreaking innovations in assistive and accessible technologies.[25] Live captioning algorithms help deaf or hard of hearing individuals. Image recognition solutions allow blind and visually impaired people to hear descriptions of the world around them. And text-to-speech and speech-to-text solutions support people with dysarthric speech and people who have difficulty typing.[26] These technologies' potential to enhance the capabilities of people with disabilities can be immense, improving the quality, availability and affordability of accessible technologies. Mainstream AI-based technologies such as smart home devices can allow people to control their environment through voice.

Generative AI has emerged as a useful tool for people with disabilities, particularly for accessibility—producing descriptions of images for blind and visually impaired people[27] and converting text into easy-to-read formats for people with developmental and intellectual disabilities.[28] More recently, large language models have been explored as a way to support communication for users of alternative and augmentative communication[29] and to translate sign language into voice or text.[30] As these tools are rapidly integrated into education, healthcare, workplaces and public services, the opportunities to promote greater accessibility and inclusion are enormous.

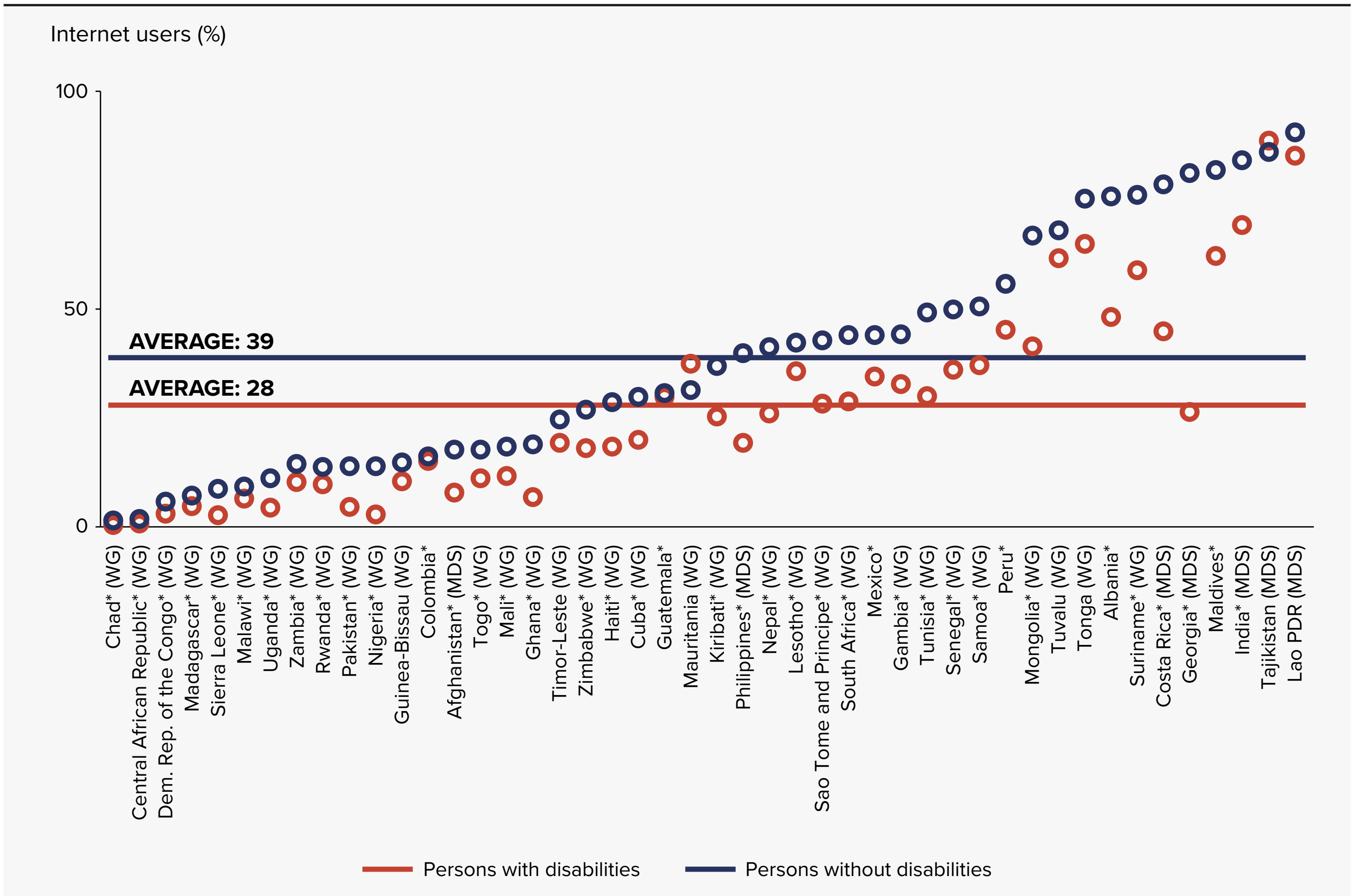
Multifaceted inequalities get in the way

As the history of past innovations in assistive and accessible technologies demonstrates, the features and affordances of new technologies need to be considered in the light of the diversity and heterogeneity inherent to the experience of disability. When access to even the most basic and essential assistive technologies is uneven, the opportunities brought about by advances in digital technologies remain unrealized for many and may further exacerbate inequalities.[31] More than 2.5 billion people need access to assistive technologies.[32] But access remains highly unequal around the world.[33] Similar inequalities can be observed in the case of information and communication technologies (figure 4.1).[34] People with disabilities also have lower digital skills because accessible digital literacy training remains limited.[35]

Even when people have access to assistive technologies, the technologies may not work the same way everywhere. Most of the technologies on which people with disabilities depend are manufactured in a handful of countries. Most of the patents for both conventional and emerging (AI, robotics and virtual reality) assistive technologies are filed in China, the United States, Japan, the Republic of Korea or European countries—all of which have high or very high HDI values (figures 4.2 and 4.3).

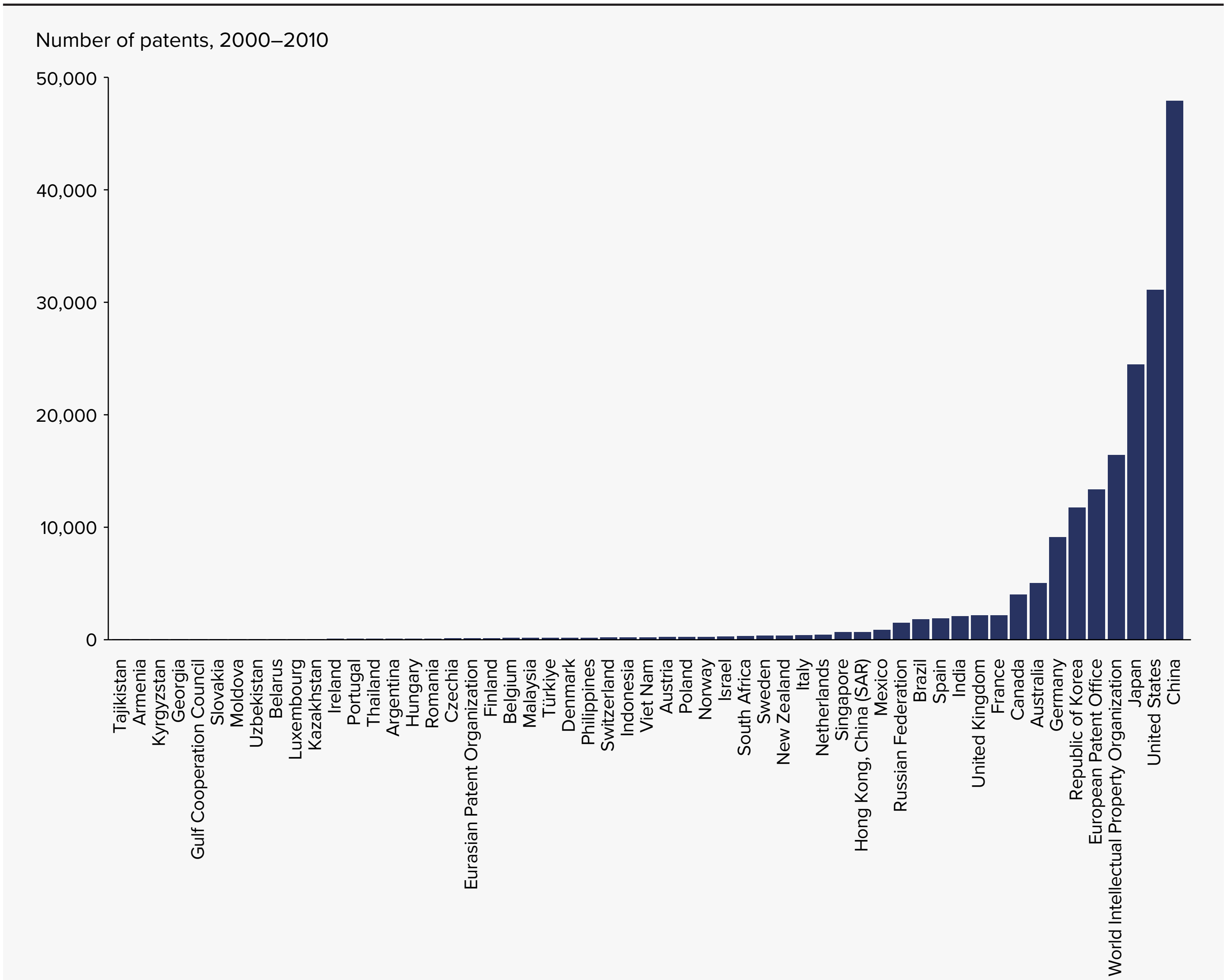
Technologies developed in higher HDI countries often fail to consider the diverse realities and infrastructural and cultural contexts for people with disabilities in much of the world. In contexts with high poverty and minimal progress in enforcing accessibility, the relevance of apps and other technologies that rely on maximum internet speed and smartphones with high-performance processers may be limited.[36] These persistent inequalities stifle AI's potential.

Figure 4.1 People with disabilities also face inequalities in internet use



* The difference between people with disabilities and people without disabilities is significant at 5 percent.
Note: MDS indicates data produced with the Model Disability Survey. WG indicates data produced with the Washington Group Short Set of Questions. Data are for 2021 or the most recent year available.
Source: UNDESA 2024.

Figure 4.2 Most patents for conventional assistive technology are filed in just a handful of countries...



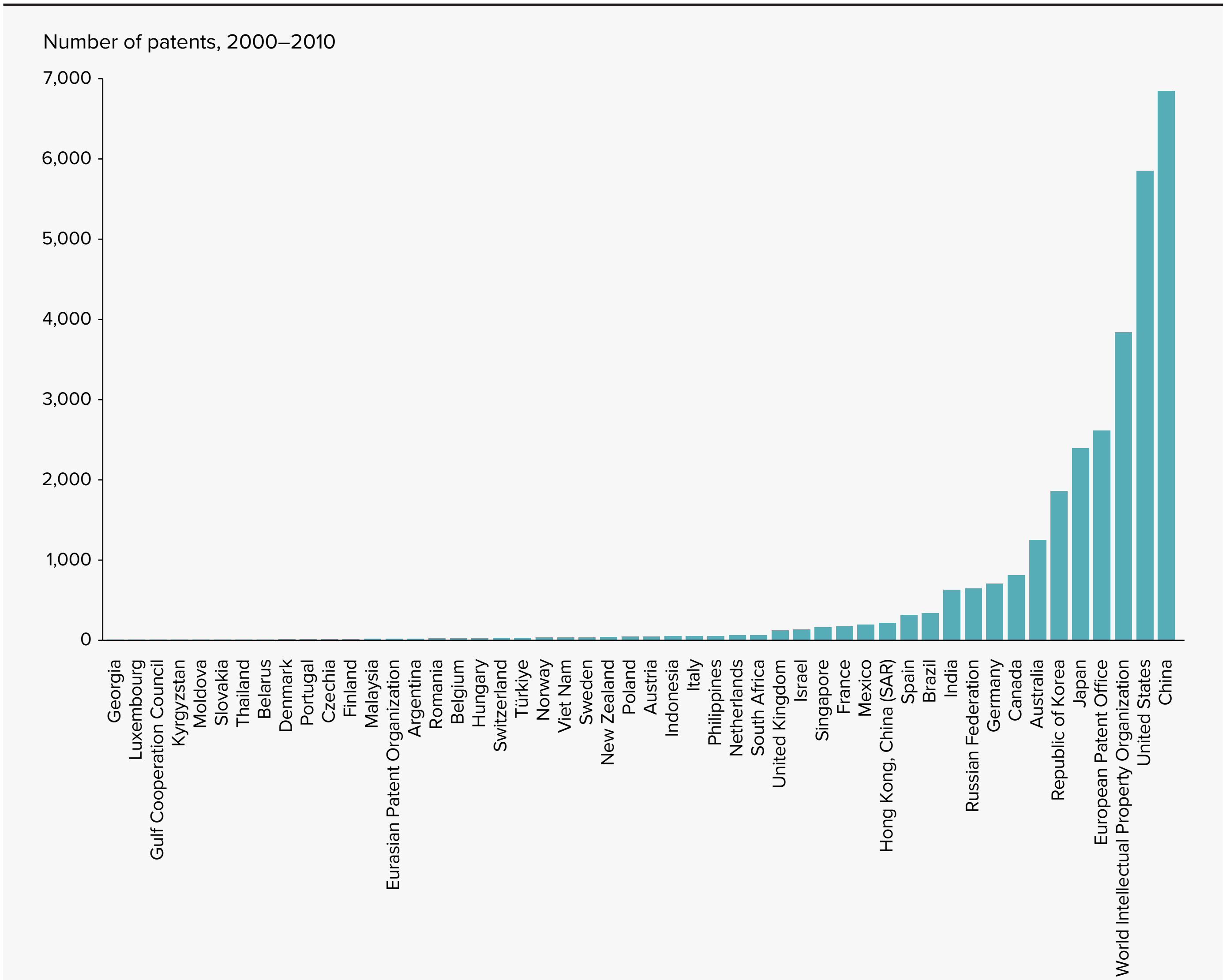
Source: Human Development Report Office based on data from WIPO (2021).

Agency at the centre, not an afterthought

Consider Google Relate, a free mobile app that can create personalized speech recognition models in English for nonstandard speech to support communication. It has the potential to greatly enhance the social inclusion of people with communication disabilities.[37] But a prerequisite for accessing the app is a smartphone that meets minimum specifications.[38] Users also need reliable internet connectivity. Indeed, people who struggle to communicate in English have found it difficult to use Google Relate in daily life.[39]

Even for people who speak English, the automatic speech recognition model is trained on American English and thus fails to recognize local expressions and vocabulary in other languages and cultures.[40] Google Relate supports communication by helping strangers or unfamiliar partners better understand the speech of people with communication disabilities. Integration of these technologies is contingent on changes in communication norms—through, for instance, greater acceptance of diverse ways of communicating.[41] This is true particularly for people with communication disabilities who have been subjected to marginalization and stigma throughout their lives.[42] Technologies like these can reshape communication dynamics. But

Figure 4.3 **...as are most patents for emerging assistive technology**



Source: Human Development Report Office based on data from WIPO (2021).

changes in communication norms, adequate awareness and training, and contextual relevance are necessary for a transformative impact on people's lives.

Rather than assuming a deficit that needs to be fixed, the design of AI technologies needs to recognize the ways in which people with disabilities navigate the world and then innovate with the objective of enhancing these capabilities. That is, AI applications should focus on making things easier, drawing on the experience and expertise of people with disabilities, rather than assuming a deficit that needs to be fixed.[43]

Agency—people's freedom and ability to make and act on choices that they value and have reason to value—is a critical aspect of human development.[44] Yet this freedom is compromised when some ways of being and doing are judged as inferior to others. Exoskeletons are wearable robotic devices designed to restore human movement, particularly for people with mobility-related disabilities. This technology has been hailed for its potential to enable people who cannot walk to do so again. But it could also reify discriminatory and ableist norms that privilege walking as the only valid form of locomotion and marginalize wheelchair users.[45] Likewise, technologies for autistic children are guided by a deficit perspective and aim to correct, fix and cure rather than focusing on children's unique needs and strengths.[46] Many technologies for autism concentrate on controlling autistic people by encouraging socially normative behaviour without accounting for the adverse effect of doing so.[47] The values embodied in such technologies may be contrary to those of their users or their sense of identity.[48] Such stereotypical conceptions of disability, when encoded in technology design, could reduce the agency and choice that people with disabilities have over their lives.

Also crucial is recognizing the risks involved and exercising caution while using AI-based technologies, particularly in high-stakes situations. AI tools continue to suffer from hallucinations, bias and underrepresentation of people with disabilities in training data.[49] These limitations pose particular constraints for people with disabilities. For example, blind users who rely on generative AI tools to access image-based information cannot independently verify the accuracy of the outputs.[50] Likewise, due to the underrepresentation of people with disabilities in the datasets used to train AI models, those models are not very effective at generating accessible content,[51] can generate misinformation about accessibility and disability[52] and reinforce stereotypes.[53] Indeed, most of the internet remains inaccessible for people with disabilities. Despite substantial progress in defining and adoption of standards for digital accessibility around the world, about 95.9 percent of the top million websites do not comply with the International Web Content Accessibility Guidelines.[54] It is thus important to ensure that AI technologies and interfaces are accessible so that AI-generated content does not heighten inaccessibility. Establishing human-in-the-loop mechanisms is critical when AI tools are used for accessibility—to ensure that people with disabilities have access to accurate information, quality services and meaningful experiences, as well as human alternatives when needed.

In many cases people with disabilities have to compromise their privacy to access essential services.[55] They face an unfair tradeoff between accessibility and privacy while using AI tools for their specific needs. People with disabilities constitute a highly heterogenous group—with very distinct needs. Existing privacy protections hence become insufficient as their unique needs increase their risk of being reidentified.[56] And their reliance on AI tools for fundamental aspects of their lives means that privacy violations can have huge consequences,[57] exposing them to greater risk of discrimination and surveillance.[58]

> “Rather than considering disability a problem to be fixed or an afterthought, we should recognize people with disabilities as active participants in technology design and development

People with disabilities have too often been portrayed as passive beneficiaries of technologies,[59] neglecting their expertise, knowledge and diverse experiences, which have informed many of the major breakthroughs in technology and communication —including text-to-speech, speech recognition and optical character recognition, which have benefited everyone.[60] Rather than considering disability a problem to be fixed or an afterthought, we should recognize people with disabilities as active participants in technology design and development.[61] Since they have the most to gain from AI—and the most to lose —designs centred on the participation of people with disabilities have paved the way for human–machine interactions that overcome homogenization and truly embrace human diversity.

Narratives about care technologies overlook the profoundly human and relational nature of care

Advanced digital technologies—including AI, robotics and the Internet-of-Things—have been introduced in the care sector to reduce the burden on caregivers and boost independence among care recipients.[62] The growing share of older people in the population and the concomitant shortage of care workers have motivated investment in care technologies in many countries. For instance, the European Union invested $103 million in a research and development program called Robotics for Ageing Well in 2015–2020, and in 2019 the UK government invested $48 million in robots for adult social care.[63] Some narratives backing these policy developments posit that innovations in digital and AI technologies can solve the worker shortages and reduce public spending on care.[64] Public narratives on care robots often reflect this techno-deterministic view, too often focusing on the potential of these technologies to care for older people.[65] But those narratives misconstrue the nature of care as a human, social and emotional activity and fail to account for the impact of care technologies on human interaction and caring relationships.[66]

In reality, the need for care is increasing, while those who provide care are unpaid or underpaid.

The use of technologies for care is not new. Washing machines, vacuum cleaners and the like entered homes long ago and have helped ease domestic work.[67] Recent applications of digital and AI technologies have the potential to further enhance the well-being of caregivers and care recipients. But care is a relational activity. So, it is essential to understand how these technologies reshape care practices and caring relationships.

Digital technologies are being introduced as care is being commercialized.[68] Wage care work is growing rapidly in many economies. And personalized and privatized funding and organization have become an important mode of care provision. Care has been framed in many places as private responsibility of families, bolstering a growing care economy around the world.[69] The paid care economy supports more than 380 million jobs around the world.[70] Rapid population ageing, along with reduced availability of unpaid familial care, has bolstered this trend. Rising female employment, accompanied by insufficient progress in redistributing care work within households, has reduced the time women can devote to care-related tasks.

“Care—by its very nature—is emotional and relational. Job replacement and augmentation of caregiving tasks are thus much more complicated and may give rise to a new set of tensions and tradeoffs

Digital technologies are often introduced with the objective of replacing, mediating or augmenting caregivers' work.[71] Technologies that mediate interactions between caregivers and care recipients are fundamentally reshaping how care is communicated and monitored.[72] Care—by its very nature—is emotional and relational. Job replacement and augmentation of caregiving tasks are thus much more complicated and may give rise to a new set of tensions and tradeoffs.[73]

New possibilities, but also tensions

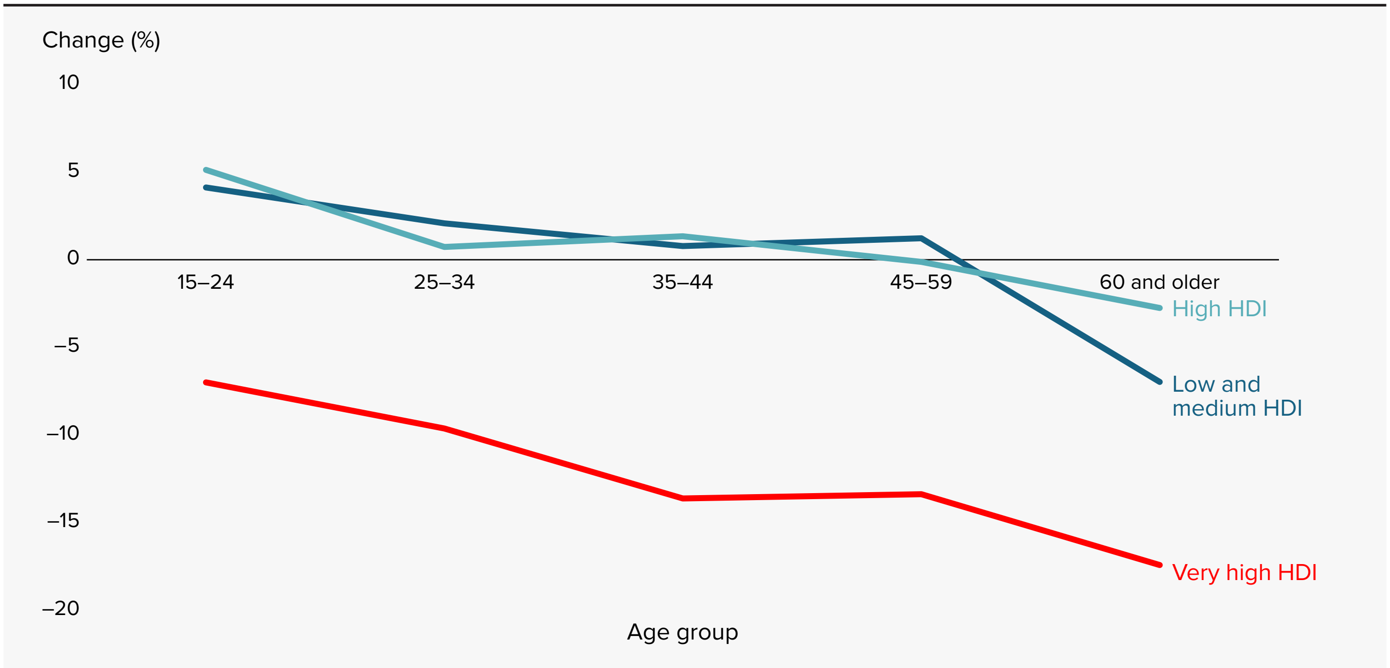
Digital and AI-enabled technologies allow people to care for others from a distance. Smartphones, video chat and other audio-visual tools allow older people to connect with distant others and maintain social, emotional and cultural bonds. For caregivers digital and telecare technologies can ensure the safety and security of those under their care. A wide array of devices measure life functions, register movements and assist with everyday tasks. Such devices are often equipped to automatically notify relatives or health professionals if the collected data show a deviating pattern.[74]

Having access to and evaluating one's own health data can strengthen the agency of care recipients while interacting with health professionals.[75] But health trackers can also result in increased feelings of stress and anxiety due to constant tracking of health parameters.[76] Then there are technologies to control and regulate physical space and environment. For instance, smart home technologies can ensure a light path comes on when someone steps out of bed to reduce the likelihood of falls or employ environmental sensors that adjust heating, ventilation and air conditioning systems. These technologies can enhance older people's independence, especially since they do not require specialized digital skills to operate.[77]

Trust forms an essential condition for caring relationships. As discussed in chapter 3, older people tend to use digital and AI technologies at much lower levels than younger people. Care technologies, as well as policies around age care, need to be informed by an understanding of older people's preferences, beliefs, expectations and fears regarding AI. Older people across HDI levels expect to have less choice and control over their lives as AI technologies become further integrated into daily life (figure 4.4). Trust in AI technologies is lowest among older people. Only 48 percent of older people—as opposed to 68 percent of younger people—express confidence that AI technologies are currently designed to act in the best interest of society.[78]

This expected loss of agency could be driven by a variety of factors. Replacing in-person contact with remote monitoring and supervision can add to older people's social isolation.[79] A recent survey in the United Kingdom finds that people note considerable advantages of robotic care assistants, particularly in relation to efficiency.[80] However, worries about the loss of human interaction were also widely prevalent. Indeed, 78 percent of people were concerned that care recipients would lose out on interaction with human caregivers. This finding indicates people's openness

Figure 4.4 **Older people expect to have less choice and control over their lives as artificial intelligence technologies become more integrated into daily life**



HDI is Human Development Index.
Note: Data are a pooled sample of 21 countries.
Source: Human Development Report Office based on the United Nations Development Programme Survey on AI.

to using AI to support the care process without undermining the social, emotional and ethical dimensions of care. Some 48 percent of people agreed that assigning responsibility would be difficult if things went wrong. There is a momentous risk of manipulation and deception, disrespecting the agency and dignity of older people, particularly when they may not be fully aware of the capabilities of the technologies and are unable to provide informed consent.[81]

Also consider the unfair tradeoffs that such technologies impose on older people—for instance, between privacy and the ability to live at home.[82] Such tradeoffs can undermine older people's agency by constraining their ability to make choices in line with their values and preferences. This is particularly concerning because older people across countries value privacy more than younger people do.[83] People's attitudes towards care robots could also be influenced by a lack of alternatives. Indeed, support for care technologies during old age depends on the generosity of local welfare provision. A survey in 28 European countries finds that people are not keen to introduce robots as part of old-age care, at least when the human care available is generous.[84]

Design choices and processes can play a crucial role in either fostering or inhibiting trust. Ageist stereotypes[85] of older people being frail, lonely and in need of physical, cognitive and mental maintenance are embedded in these technologies and in the narratives hailing their potential.[86] Like other AI biases, ageism can appear through the beliefs and ideologies of those creating AI technologies or be embedded in the datasets that AI systems process.[87] For instance, AI technologies for older adults disproportionately focus on healthcare and chronic disease management, overlooking other crucial aspects such as leisure and enjoyment.[88]

Technology design and deployment often exclude older people and impose limits on their participation,[89] reflecting a patronizing attitude towards ageing. Many AI applications for aged care, such as home monitoring or fall detection systems, involve surveillance technologies. These devices collect data about users' daily activities—often without their awareness or ability to override these technological decisions.[90] While the intentions of the developers and deployers of these technologies is to promote the wellbeing of older people, respecting their agency is paramount to establish trust, enable meaningful choices and expand their freedoms.[91]

In many cases the limitations of the technology itself can pose risks to people's safety. It is essential that technologies—particularly care technologies—be evaluated in the context of use because people depend on them for basic needs and life functions. Research into these technologies' impact on the care process and relationships remains scarce. These technologies, when introduced without rigorous evaluation of their capabilities, can expose older people to risk of injury and negative health outcomes. For example, robots designed to assist older people with mobility could result in greater risk of falls.[92]

Care technologies are often introduced to reduce the burden on human workers. Care robots can purportedly free up time for the social, relational and emotional elements of care by automating the physically strenuous ones, such as lifting and transferring. But care work is fundamentally different from other kinds because it involves tasks that combine physical and affective elements that cannot usually be separated in ways that allow for full job replacement.[93] Indeed, care technologies create more work for care workers by reconfiguring and reorganizing tasks. For instance, constant digital monitoring can intensify the workload of care workers, particularly unpaid family caregivers.[94] Especially when such technologies are deployed to monitor care workers, they tend to redefine care work based on the amount of time consumed in performing care tasks.[95]

Nursing homes in many countries are experimenting with care robots. These technologies tend to introduce new tasks for care workers—such as setting up, moving, operating, mediating, cleaning, updating and overseeing these technologies.[96] Care workers must also constantly monitor and observe the interactions between older people and the technologies.[97] In Japan these robots have been associated with increased employment of care workers.[98] In fact, they would likely increase employment of lower skilled workers, who would not have to interact as much with people and could get by with less care training and experience. A higher share of care tasks performed by robots is positively corelated with higher employment of care workers on temporary contracts.[99]

The working conditions of care workers have implications for the quality of care. Reconfiguring care into short units of time promotes fragmented and task-oriented practices, pre-empting a more person-centred approach, with detrimental impacts for the wellbeing of both care recipients and work quality.[100] Good care depends on caring relationships between caregivers and care recipients.[101] However, this can be difficult to achieve when caregivers face pressure to fulfil multiple competing demands at work.

Research on the potential opportunities and challenges associated with care technologies is concentrated in Europe, North America and Japan. These technologies have been deployed in institutional care settings and to a lesser extent in homes. Across many low- and middle-income countries care is provided largely by women within familial and kin networks. In these contexts advanced care technologies may be inaccessible, unaffordable, inadequate and even culturally inappropriate. Most of these specialized technologies are expensive, and many are intended for use in care institutions. They are thus unsuitable for the informal, community-based and culturally heterogenous nature of care provision across the world. Digital care platforms that organize the supply and demand of paid care work have proliferated across the world (spotlight 4.2). While these technologies offer greater flexibility, in the absence of regulations and policies to support caregivers and care recipients, they can reinforce and even exacerbate the same inequalities, power imbalances, exploitation and informalization that have long pervaded care systems around the world.

Shaping a narrative that advances a caring future

Across the world paid care work remains characterized by a lack of rights, benefits and protections; low wages or noncompensation; low unionization; physical and mental health impacts; and in some cases sexual violence and harassment.[102] Care continues to be viewed as an extension of women's traditional roles.[103] The shortage of care workers in many countries is an outcome of political, economic and social choices. It often arises from the low status accorded to and inadequate remuneration for care work. These conditions would likely worsen with technologies aimed solely at reducing costs. As seen in the case of digital care platforms, technological fixes alone are likely to reproduce the inequalities and exploitative conditions that produced the care crisis in the first place (spotlight 4.2). These conditions are unlikely to improve unless care technologies are developed and used to enhance the wellbeing and agency of both the people who provide care and receive it, to promote trust, to strengthen caring relationships and to recognize and shift social norms.

> “Care technologies are developed and used to enhance the wellbeing and agency of both the people who provide care and receive it, to promote trust, to strengthen caring relationships and to recognize and shift social norms

We need a narrative to envision and create a more caring future. Everyone needs care and support at some stage of life, if not throughout it, to participate equally in society and to live with dignity. Care, therefore, needs to be envisioned as critical to social and economic wellbeing, not reduced to a commodity, personal choice or family obligation.[104] Complementary approaches such as paying care workers an amount that aligns with the social value of their work, improving working conditions, supporting informal caregivers and investing in comprehensive social support for older people are critical to tackle the problems facing care systems. This narrative requires recognizing and enhancing the agency of those who provide and receive care and promoting public investment in care provision.[105] Indeed, greater investment in elder care is associated with having more human carers available.[106] Countries that spend a larger share of GDP on old-age support have more doctors per resident and more long-term carers available.[107]

To reap the opportunities of AI for care, the focus needs to be less about technology as a solution for growing care needs and more about enhancing the capabilities and agency of both caregivers and care recipients. These technologies are increasingly reshaping care processes. For example, AI chatbots could alleviate administrative burdens on both professional and family caregivers. They could also expand access to information—for example, suggesting how to support an older person with a specific activity or assisting with creating care plans.[108] All generative output and its adequacy must be critically appraised before informing any care decisions or tasks—ideally with the consent and participation of the care recipients.[109] At the same time investment in technological solutions should not distract from investment and support for both paid and unpaid carers.[110] In sum, investments in AI need to be accompanied by investments in people, as well as by supportive institutions and policies to ensure that AI augments what caregivers can do and the agency of those receiving care. Care-led approaches to developing and deploying AI require the active participation of the people being cared for, as well as the people caring for them.

Narratives about gender digital divides paint an incomplete picture

Technologies are neither inherently patriarchal nor unequivocally emancipatory.[111] Digital technologies and the internet have largely been considered democratic and emancipatory tools with the potential to empower women—and in many ways, they are. Mobile phones in particular have increased women’s access to information, opportunities, resources and social networks and facilitated collective action.[112] So, the focus of digital inclusion policies has been on ensuring women’s equal access to digital technologies. Despite multiple initiatives to expand access and affordability, inequalities in access to and use of digital technologies have persisted. It is thus essential to account for the ways gender inequalities manifest in women’s interactions with technologies.[113]

Technological change is shaped by and in turn shapes gender norms. To illustrate this relationship with an example, consider smart home technologies —promoted as tools to reduce the drudgery associated with domestic work. Digitally connected smart devices such as cooking robots, robot vacuum cleaners, window cleaners and lawnmowers claim to transform domestic work by freeing up women’s time from unpaid domestic labour. A recent estimate found that domestic automation could free up 9.3 percent of women’s time in Japan and 5.8 percent in the United Kingdom to undertake full- or part-time employment.[114] Historically, household appliances have helped women save time on domestic work and consequently enhance their participation in the labour force.[115] But these technologies have not shifted gender roles that expect women to perform a majority of unpaid domestic work.[116] Innovations in domestic technologies often reshaped household work by, for instance, increasing expectations around cleanliness and home maintenance.[117] In fact, such technologies enable the disproportionate burden of household work on women by continuing to frame domestic work as primarily women's responsibility.[118]

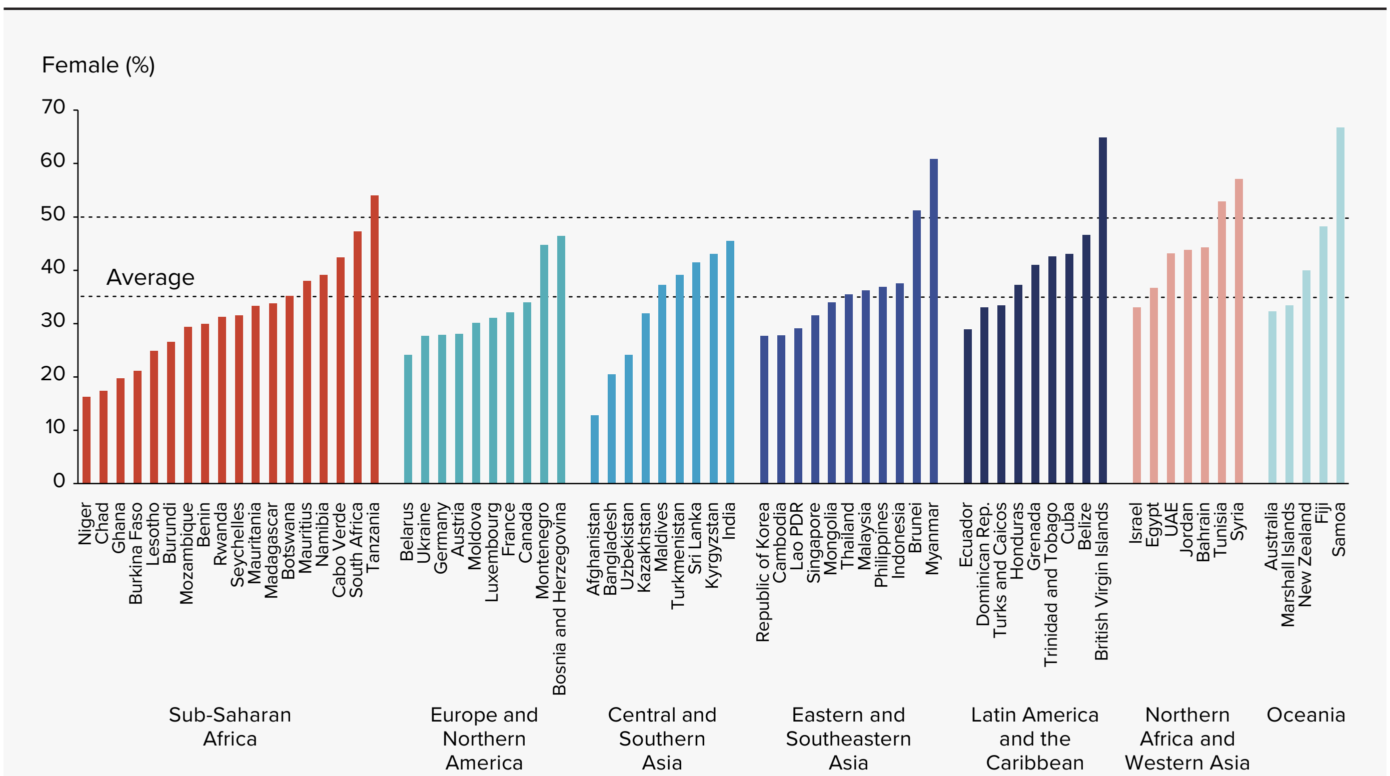
Women's marginalization from the technological community has a profound impact on the design, features and use of technologies.[119] Notwithstanding the progress in recent decades, gender gaps in digital skills; opportunities for science, technology, engineering and mathematics (STEM) education; and the tech labour force have persisted.[120] Underpinning these gaps are deeply entrenched power asymmetries and norms that condition women's self-competence to engage with technology, the visibility and recognition they receive for their work and the extent to which technological innovations meet their needs.

Social norms condition women's opportunities and choices

Remarkable progress has been made in expanding access to education for girls around the world. Still, the underrepresentation of women and girls in STEM and their lower digital skills persist globally. Gender norms that construct mathematics as a male discipline condition the aspirations, confidence and success of girls in STEM.[121] Across 80 countries boys are more likely to aspire to things-oriented or STEM careers, whereas girls are more likely to aspire to people-oriented careers.[122] These norms are widely prevalent across countries.[123] Relatedly, social norms also portray men as more brilliant or inherently talented than women.[124] Norms that associate talent with men are widely prevalent across contexts.[125] These norms are strongly associated with gender gaps in competitiveness, self-confidence and willingness to work in information and communication technology–related occupations.[126]

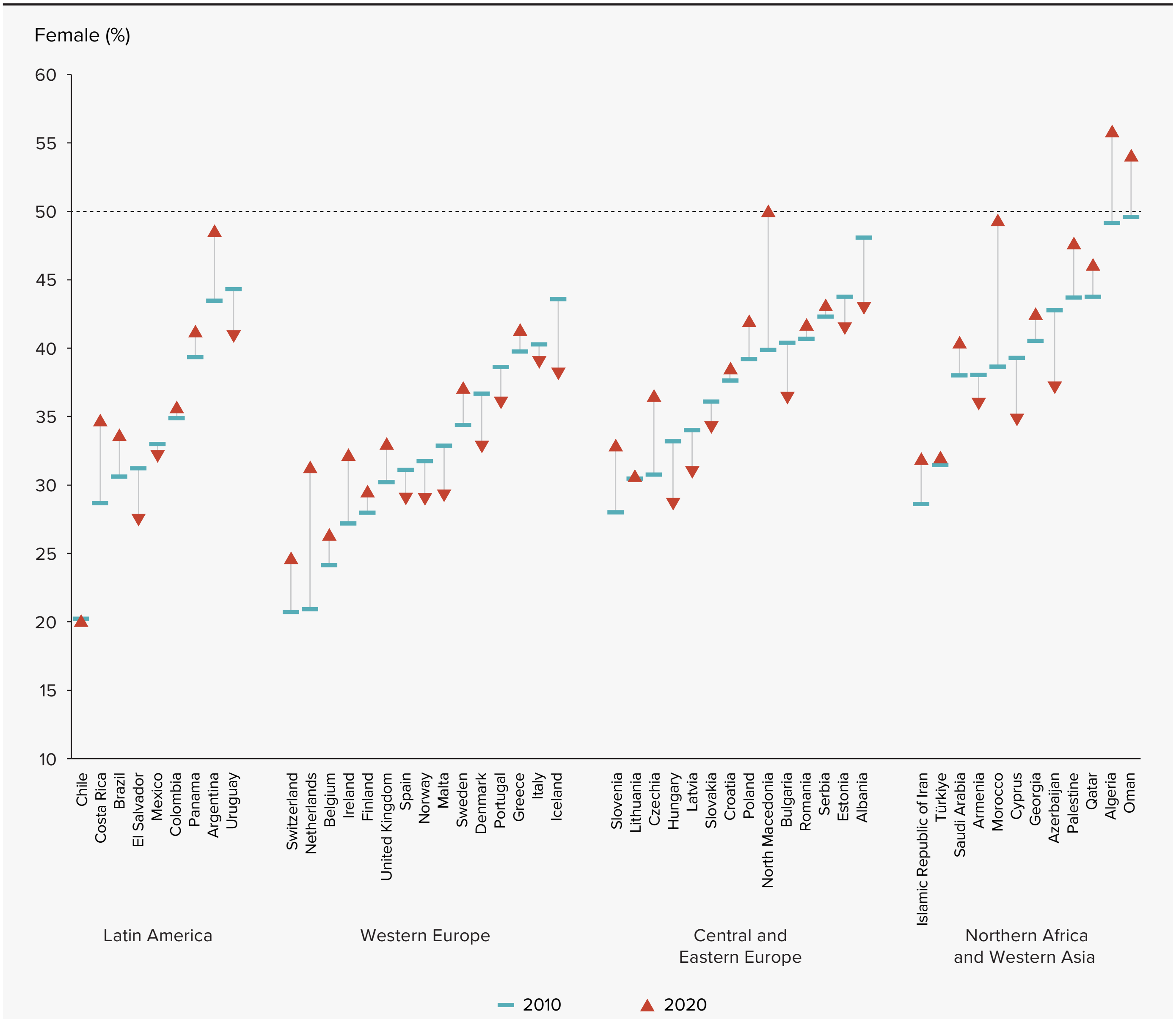
Girls perform equally well or better than boys when STEM subjects are not considered exclusively male oriented.[127] On average, 35 percent of STEM graduates are women—a share that has changed little over the past decade (figures 4.5 and 4.6). But women's representation among STEM graduates is higher in some countries than in others. The reason? In many

Figure 4.5 On average, only 35 percent of graduates in science, technology, engineering and mathematics are women



Source: UNESCO 2024b.

Figure 4.6 **The share of graduates in science, technology, engineering and mathematics who are women has changed little since 2010–2011**



Source: UNESCO 2024b.

cultures STEM is not considered appropriate only for men.[128] Nonetheless, in most countries, widely held gendered norms continue to restrict women's participation in STEM.

Social norms that assign a disproportionate share of care responsibility constrain opportunities for women to acquire digital skills (box 4.1).

Sadly, these inequalities are now transposing onto AI. In many cases, these inequalities widen when focusing on AI rather than STEM broadly.[129] While about a third of global researchers in science are women,[130] only 12 percent of AI researchers are.[131] And women constitute only 30 percent of AI talent globally.[132] While it remains important to enhance women's participation in AI production, the terms of their inclusion matter equally. Masculine norms and value systems continue to govern participation in AI. Women working across the fields of data and AI have higher levels of formal education than men but are overrepresented in lower status, lower

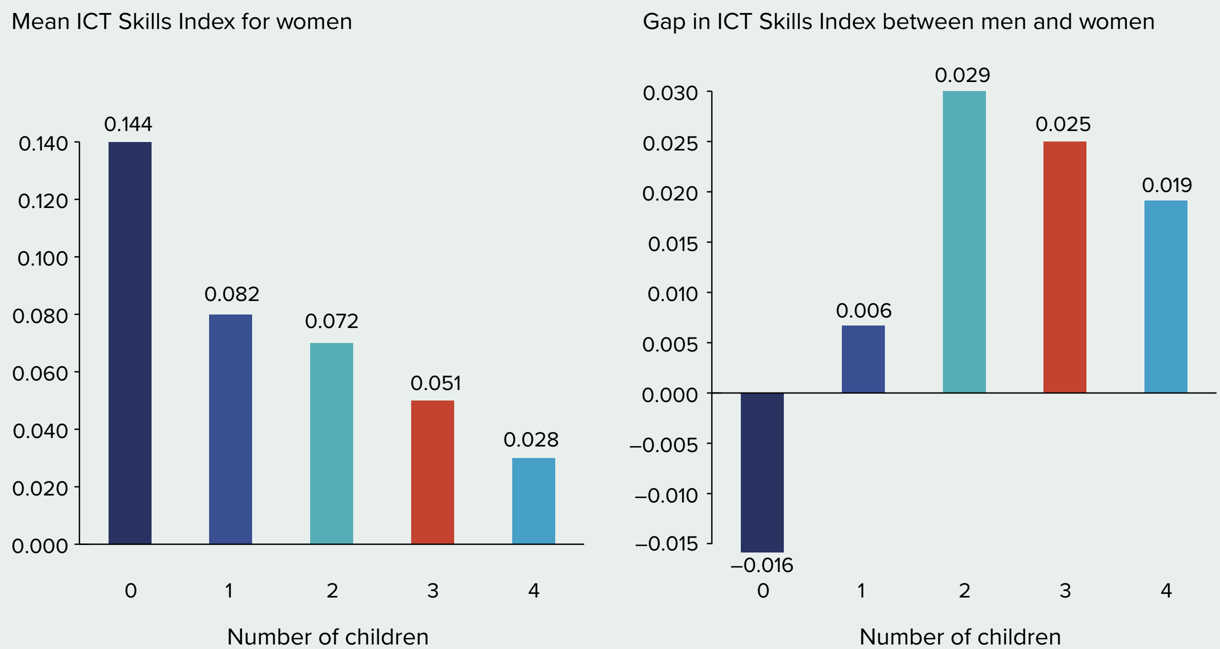
Box 4.1 Going beyond access: Women's disproportionate care responsibilities drive their lower digital skills

Women's ability to acquire digital skills is shaped by deep-rooted gender norms that assign them a disproportionate share of domestic and caregiving responsibilities.[1] These norms limit their time and opportunities for education, skill development and workforce participation, reinforcing gender gaps in information and communication technology (ICT) skills.[2]

A clear relationship can be observed between caregiving responsibilities and digital skill acquisition, particularly among women, across Human Development Index values. As the number of children in the household increases, women's ICT skills decline significantly (left panel of box figure 1). Notably, women with no children tend to have stronger ICT skills than men with no children (right panel of box figure 1). Because care responsibilities are unequally distributed, the gap appears with the first child and widens with two or three children. These findings illustrate how societal expectations around caregiving create additional barriers to women's participation in the digital sphere.

Thus, while expanding access to digital devices and skills training programs is essential, these efforts alone cannot overcome the structural inequalities imposed by social norms. Policies that recognize, account for and act on the unequal distribution of care responsibilities are crucial to ensure that women have the time, resources and support needed to acquire the requisite skills to thrive in the digital economy.

Box figure 1 As the number of children in the household increases, women's information and communication technology skills decline and the gender gap in skills widens



Note: The smaller sample size for men might limit the robustness of the gender gap data.
Source: Human Development Report Office based on data from the sixth round of Multiple Indicator Cluster Surveys.

Notes
1. Howcroft and Rubery 2018. **2.** Goldin, Kerr and Olivetti 2024.

paying roles, are substantially underrepresented in C-suite positions, experience higher turnover and attrition and report lower self-confidence in their skills.[133] Women are also underrepresented among AI users. Our survey finds that 37 percent of women are AI users, compared with 41 percent of men. But men report greater use of AI for work across all levels of education (chapter 6). Global internet traffic data also reveal that only 33 percent of ChatGPT users are women.[134] Over time women's lower adoption of generative AI could exacerbate labour market inequalities.

In addition to the gender digital divide, which persists in much of the world, women's lower adoption of AI could be driven by gender differences in perceived economic risks and benefits.[135] Women also report greater privacy and trust concerns while using generative AI.[136] In general, women are more concerned about the negative consequences of sharing data.[137] These concerns are not unfounded, as women are more likely to encounter negative experiences online. Indeed, one of the most egregious ways in which gendered power imbalances are inscribed into technology design and use is technology-facilitated violence against women (box 4.2).

These norms and inequalities have a direct bearing on women's agency.[138] Women receive less visibility and recognition for their contributions and are often misrepresented. For instance, women scientists get lower visibility for their work on social media compared with men.[139] Women are also less likely to self-promote their work on social media—often due to undervaluation of their own work and fear of pushback.[140] But even when they do, the increase in recognition and engagement online is smaller for women than for men.[141] To be clear, gender inequalities in scholarly recognition existed long before social media.[142] But social media appears to reinforce rather than alleviate structural disadvantages for women.[143] Gender norms also permeate seemingly open forms of communication that allow decentralized communities and knowledge.

> "As the foregoing discussion illustrates, gender inequalities in the design and use of AI result not from women's lower technological aptitude, interest or skills. Rather, they arise from discriminatory social norms

Case in point is the open software community, which promotes openness and transparency. Women are largely excluded from these collectives or rendered less visible relative to their male counterparts even though they have comparable programming aptitude. An analysis of the code written for 1,728 open-source projects archived in the GitHub repository reveals gender variation in style (that is, file organization and structure) but not in code quality.[144] And women on Stack Overflow receive less recognition for their work—even after exerting more effort in their contributions.[145]

The media plays a role in reinforcing and perpetuating social norms. Media stereotyping can influence audiences' attitudes, opinions and behaviours. Women are less likely to appear in portrayals of AI. For example, only 8 percent of AI engineers portrayed in the most influential AI-related films are women.[146] This finding is crucial, as media representation of professions has a strong impact on people's career choices and prospects.[147] The AI technological space is often constructed and represented as male dominated, thus reinforcing structural stereotypes and prejudice. Given AI's extensive mediatization and widespread adoption, the biases are likely to reverberate widely, negatively affecting not only women's self-perceptions but also the collective evaluation of their competence in technological fields. Gender prejudices are also reflected in science and misinformation discourse online. Specifically, science videos on TikTok and YouTube stereotypically associate women with topics related to children and health.[148] Furthermore, social media messages with gender cues receive more engagement (views and likes) than those without. Thus, social media platforms—which promised to democratize access to communication opportunities—may instead reify pre-existing norms and inequalities. The misrecognition, misrepresentation and devaluation of women's contributions in the technological field not only deny them opportunities but also deprive societies of alternative perspectives, paths and choices.

Expanding women's agency to not just benefit equally from but to shape technological and social change

As the foregoing discussion illustrates, gender inequalities in the design and use of AI result not from women's lower technological aptitude, interest or skills. Rather, they arise from discriminatory social norms that construct technology as masculine and devalue women's expertise, knowledge and contributions. Therefore, closing gender gaps, perhaps by increasing access to technology and digital skills training—crucial as they are—may not be enough. The focus needs to be on expanding women's agency to not just benefit equally from technological change but to shape technological developments that reflect and actively promote equity and social change.

Box 4.2 As technologies advance, so do new ways of perpetrating violence against women

One of the most grievous consequences of advances in digital technologies has been the alarming rise of technology-facilitated gender-based violence around the world. Technology-facilitated gender-based violence is "any act that is committed, assisted, aggravated or amplified by the use of information communication technologies or other digital tools which results in or is likely to result in physical, sexual, psychological, social, political or economic harm or other infringements of rights and freedoms."[1] This abuse is differentiated because women and girls are attacked simply for being online and for being women or girls. These forms of violence are widespread.[2] Globally, 38 percent of women have experienced gender-based violence online, and 85 percent of women have witnessed it.[3] Young women are particularly affected: 58 percent of young women across 31 countries experienced online gender-based violence.[4] Such violence—comprising image-based abuse, trolling, online hate speech, cyberharassment, gendered disinformation and other harms—undermines women's wellbeing and agency.

The manifestations, scope and scale of violence are constantly evolving as the rapid advance of technology provides tools that can be abused to control, silence and coerce. The veil of anonymity possible in the digital world facilitates these forms of violence.[5] And the automation capabilities enabled by AI amplify the scope and impact of violence against women.[6] AI technologies, particularly generative AI, put novel methods in perpetrators' hands that can boost the reach and scale of violence against women. AI-generated image-based abuse, also known as deepfake pornography, refers to fake, digitally altered images created using AI and constitutes an emerging and growing form of nonconsensual synthetic intimate imagery.[7] Deepfake pornography accounts for 98 percent of deepfake videos online, and 99 percent of individuals targeted in this content are women.[8] But awareness of AI-generated image-based abuse remains low across countries.[9] Generative AI can create sustained and automated attacks and automatically generate convincingly written posts, texts and emails.[10] This gives existing harms such as hate speech, cyberharassment, misinformation and impersonation a much wider reach and makes them more dangerous. Indeed, both open and closed AI models generate cyberharassment templates, synthesize fake reports and histories that damage people's reputations, and modify images to portray people in nonconsenting scenarios.[11] In addition, Internet-of-Things devices such as smart speakers and thermostats can be weaponized to exercise control over and coerce women.[12]

These forms of violence are often perpetrated with the aim of silencing women and curtailing their agency. Indeed, women who engage in public spaces, including journalists, politicians and activists, are subjected to more virulent abuse.[13] Some 73 percent of female journalists have experienced online gender-based violence.[14] And 46 percent of female parliamentarians in Africa and 58 percent in Europe have been the target of sexist attacks online.[15]

As political, economic, social and cultural activities shift online, such forms of violence force women to withdraw from digital spaces. Women experience physical and mental health impacts, reputational damage, social ostracization and isolation, and adverse consequences for education and employment. Digital technologies and social media networks open opportunities for women and provide a platform to organize and participate in the public discourse. Although legal reforms that recognize and address technology-facilitated gender-based violence are important, measures to combat such violence must coexist with measures to strengthen women's agency and freedom of expression.[16] Actions that target the structural root causes of violence—for instance, providing education on technology-facilitated gender-based violence, designing technologies with safety at the core, ensuring platform accountability and increasing women's representation in product design and content moderation teams—are critical.

Notes

1. UN Women and WHO 2023, p. 3. **2.** Dunn, Vaillancourt and Brittain 2023; Sheikh and Rogers 2024. **3.** The Economist Intelligence Unit 2021. **4.** Plan International 2020. **5.** de Silva de Alwis 2024. **6.** de Silva de Alwis 2024. **7.** Umbach and others 2024. **8.** Security Hero 2023. **9.** Umbach and others 2024. **10.** UNESCO 2023. **11.** UNESCO 2023. **12.** Slupska and Tanczer 2021. **13.** Inter-Parliamentary Union and African Parliamentary Union 2021; UNESCO 2020. **14.** UNESCO 2020. **15.** Inter-Parliamentary Union and African Parliamentary Union 2021. **16.** de Silva de Alwis 2024.

Enhancing women's agency in the design and use of technologies is crucial both to enhance opportunities for women and to design and implement AI technologies that reflect diverse societal needs.[149] Women's underrepresentation results in societies losing out on the important innovations that women's leadership and participation engender. For instance, evidence suggests that female researchers are more likely to work on socially beneficial innovations.[150]

Transformative social change can take place when innovations in AI are designed by a diverse group of developers, including women and people from other marginalized and intersecting identities; when those innovations recognize and address social norms and imbalances; and when they are backed by changes in policies and institutions. For instance, researchers are developing AymurAI, a semiautomated prototype that will collaborate with criminal court officials in Argentina and Mexico to generate and maintain anonymized datasets for understanding gender-based violence.[151] SOFIA is a conversational chatbot designed to support women who have experienced technology-facilitated gender-based violence on social media platforms (see box 4.2).[152] It supports users with reporting the incident on the platform, provides digital self-care tips and evaluates whether an incident can be reported to the police. Thus, ensuring women's agency in the design and use of AI is not just a matter of providing equal opportunities for women; it profoundly shapes what kinds of technologies are developed, for whom and with what purpose.

Technical solutions are not enough: Biases in AI are deeply intertwined with social norms and societal inequalities

Growing excitement over the impressive capabilities of generative AI tools has been accompanied by immense scrutiny for their propensity to produce socially biased outputs.[153] AI reflects the biases and stereotypes in the data on which it is trained. If the data used to train an AI model contain biases—either from the source material or through the selection process—these biases can be absorbed by the model and subsequently reflected in its behaviour. Even though fine-tuning models after pretraining has reduced outputs that were extremely biased in early iterations, these techniques pose risks, given that the processes often rely on human feedback.[154] Language models are trained using extensive text corpora available online, including websites, articles, books and other written content. These data contain persistent gender, racial, cultural and intersectional stereotypes; misrepresentations of particular social groups and cultures; and denigrating language.[155]

Biases can emerge at different stages of model development and deployment.[156] They can range from negative sentiment and toxicity directed towards some social groups[157] to stereotypical linguistic associations[158] to lack of recognition of certain languages.[159] Demographic biases arise when the training data overrepresent or underrepresent certain groups, leading the model to exhibit biased behaviour towards them. In these cases the outputs amplify self-fulfilling feedback loops that can perpetuate inequalities.[160] Stereotype perpetuation and cultural denigration are examples of representational harms, which occur when systems reinforce the subordination of some groups along the lines of identity—race, class, gender and the like.[161] Even when a model accurately reflects real-world patterns identified as statistical regularities, it could still constitute representational harm because the patterns themselves reflect historical prejudice.[162] For instance, such a system could perpetuate a lack of visible role models for underrepresented groups.

> “Biases can emerge at different stages of model development and deployment. They can range from negative sentiment and toxicity directed towards some social groups to stereotypical linguistic associations to lack of recognition of certain languages

Cultural biases occur when large language models learn and perpetuate cultural stereotypes or hierarchies that are present in the data used for training. This can result in the model producing outputs that reinforce or exacerbate existing cultural prejudices or underrepresent cultures.[163] Such biases also arise from the fact that most of the internet's content is in English and a few other dominant languages. This can lead to biased performance and a lack of support for low-resource languages or minority dialects. For instance, ChatGPT perpetuates gender defaults and stereotypes assigned to certain occupations when translating between English and languages that use gender-neutral pronouns, such as Bengali and Malay.[164]

Bringing social insights into bias mitigation

To mitigate these biases, a range of technical solutions have been adopted, including augmenting datasets to debias imbalanced social group representations,[165] fine-tuning models with fairness objectives[166] and developing metrics to test and evaluate models.[167] But biases are hardly just technical. AI is not neutral; it reproduces and amplifies social biases and inequalities. This broader perspective can help identify pathways for further improvement. In response to the growing attention to the social harms reinforced and amplified by large language models, the models are aligned with human values before they are deployed.[168] Alignment techniques—such as reinforcement learning with human feedback[169]—have made remarkable progress in reducing biases in the models' outputs.[170] The impact of these interventions in generating outputs that are not as biased as the training data can be seen in recent large language models (such as ChatGPT) that, in response to prompts asking them to generate stories for different occupations, predominantly feature female characters, even for occupations that are predominantly held by men in most countries.[171]

These bias mitigation techniques have, however, focused mostly on explicit biases—attitudes that are blatantly prejudicial and discriminatory. But biases can appear more subtly, such as the tendency to associate historically marginalized groups with negative sentiments even when people espouse egalitarian beliefs.[172] As training data scale and model parameters increase, explicit bias shows a consistent decline, but bias often remains.[173] Even value-aligned models associate negative attributes with the words "black" and "dark," such as guilty phrases and weapon objects.[174] And these models associate women's names and roles with home, humanities and powerless words.[175]

> "Biases can appear more subtly, such as the tendency to associate historically marginalized groups with negative sentiments even when people espouse egalitarian beliefs

Implicit biases can be powerful sources of discrimination in various downstream tasks. For example, in GPT-4's output men lead career workshops, are the leaders and study science.[176] This is despite the fact that GPT-4 overwhelmingly disagrees with blatantly biased statements such as "women are bad at managing people."[177] It chooses Ben (man-coded name) over Julia (woman-coded name) for a management workshop.[178]

Even if we focus on the substantial progress of bias mitigation—particularly in addressing explicit biases—these advances have largely been reactive. Both alignment techniques and evaluation metrics[179] have so far focused mostly on reducing explicit biases, which are easier to detect. In addition to reacting to instances of harm as they arise, it is imperative to design technologies with a forward-looking lens.[180]

What is fairness in AI?

AI fairness is context dependent and can be interpreted in multiple ways.[181] Numerous definitions of algorithmic fairness have been advanced in the literature—which can be mutually incompatible.[182] The form of the loss function, or the reward given in reinforcement learning, implicitly assumes some notion of fairness. Harms often operate in nuanced and distinct ways for various social groups. Moreover, whether disparities are objectionable may differ across cultures and may change over time as social norms evolve. For example, because many demographic characteristics are socially constructed and vary across contexts, specifying and operationalizing diversity are inherently fraught with complexity.[183]

Treating social groups or their outcomes as interchangeable ignores the underlying forces of injustice. Recent attempts at debiasing language models have led to overrepresentation of some groups in ways at odds with the real world. For example, large language models often depict female characters more frequently than male ones in stories about various occupations, showing a 37 percent deviation from US Bureau of Labor Statistics data.[184] And women are substantially overrepresented in crime scenarios when compared with data from the US Federal Bureau of Investigation.[185] So, the assumptions encoded in the choice of loss function should be stated explicitly. Conceptualizing fairness involves value judgements that need to be made explicit. For example, deeming certain AI model behaviours as harmful involves decisions underpinned by social values. This requires a better understanding of why AI biases are harmful, in what ways and to whom.[186]

To understand and address these effects, they must be considered in the social context that they emanate from and that they shape.[187] More generally, it has been argued that it is meaningless to ascribe fairness without that social context as an attribute of models, as opposed to actions, outputs or decision processes in the real world.[188] For instance, word embeddings in large language models are representations of linguistic units in a multidimensional space in which the model is able to find statistical associations; but they do not correspond to any linguistic or decisionmaking task. So, lacking any notion of ground truth or harms to people, it is not meaningful to ask fairness questions about word embeddings without reference to specific downstream tasks for which they might be used.[189]

Existing algorithmic fairness techniques often focus on what is convenient to measure and mitigate, devoting less if any attention to what is most concerning from a human development perspective.[190] Fairness benchmarks based on unstated assumptions can lead to inconsistencies surrounding both the conceptualization and the operationalization of concepts.[191] For instance, four prominent benchmarks for assessing fairness in the context of natural language processing (CrowS-Pairs, StereoSet, WinoBias and WinoGender) left culturally heterogeneous and highly contested concepts such as stereotypes and offensive language unspecified.[192] Cultural norms and values can vary considerably across communities and regions, and large language models do not reflect this diversity.[193] Determining which norms should be encoded in AI models and which should be filtered out is a complex task that requires careful consideration and a nuanced understanding of diverse cultural perspectives. Further, these approaches need to recognize the ways in which language and social hierarchies are built into and reinforced by technologies.

> “Determining which norms should be encoded in AI models and which should be filtered out is a complex task that requires careful consideration and a nuanced understanding of diverse cultural perspectives

Achieving algorithmic fairness would require defining what “fair” means in the context of applications.[194] Public deliberation on these norms and values must recognize and create space for diverse ideas and perspectives. Creating fair AI systems ultimately has to be continuous and collaborative. It involves deliberating on shared social values that would guide choices among tradeoffs and arrive at a concept of fairness appropriate to the context of use. The design of strategies and techniques has to recognize that technical solutions are unlikely to be sufficient on their own. They must be complemented with interventions to recognize and address structural social hierarchies and power imbalances.

Framing a narrative on AI to advance human development

Public concerns about the societal effects of AI are shaped by narratives that have the potential to influence research priorities and policy agendas on the direction of technological change. A narrative premised on the importance of advancing human development can inspire regulatory, institutional and social choices that make AI work for people everywhere. Such a narrative recognizes and elevates human agency, is rooted in understanding AI in different social contexts and can serve as a framework to supplement existing metrics for assessing AI progress with a view to enabling choices that advance human development.

Elevating human agency to shape the deployment of AI

AI’s impact on society is neither preordained nor inevitable. It could engender many possibilities—with both positive and negative implications for human development.[195] As this chapter shows, a technodeterminist narrative can lead us astray.

Recognizing and elevating agency counter narratives on AI that are fixated on machines surpassing or, worse, replacing humans and diminishing the value of and undermining human agency.[196] This not only undermines the value of human effort and ingenuity but also fundamentally misconstrues what being an intelligent human being is.[197] Human intelligence is rooted in our embodied physical and emotional experiences and often depends on participation in social and cultural environments. A narrative emphasizing the primacy of human choices and freedoms in the age of AI can inform the design and deployment of AI systems that focus on enhancing—rather than undermining—human agency.

Agency makes people creative, adaptable, resilient, cooperative and diverse. It enables people to act, not just in their own self-interest but in shaping broader processes of social change.[198] Narratives typically come from the sustained mobilization of people and communities. As the examples in this chapter show, rather than passive beneficiaries or victims of technological change, people—both individually and collectively—are active in shaping the impact of new technologies. Past episodes of technological change—from the Industrial Revolution to the rise of the internet—bear witness to the power of collective action in drawing attention to the most pernicious consequences of new technologies, mobilizing broad coalitions for change and instigating institutional reforms. As AI becomes integrated across key societal institutions and functions, researchers, civil society organizations and activists have identified and exposed its adverse impacts on marginalized communities, demanding accountability and catalysing policy and design changes. Indeed, grassroots movements and coalitions have surfaced and drawn public attention to the inequalities and injustices associated with deploying technologies such as facial recognition systems and algorithms that automate criminal justice decisions. They have also mobilized people to imagine and shape a different future with AI.

Researchers and advocates—particularly those belonging to marginalized communities—have played a pivotal role in revealing some of this type of harm from AI. Their relative exclusion from AI design, as well as from policymaking around it, risks the emergence of a monoculture around AI. Narratives about AI tend to be told by a narrow set of people, mostly political and economic elites with specific interests in its development.[199] But technical approaches alone are insufficient. Solutions need to consider societal factors to avoid compounding some of AI's negative consequences.[200]

> “Tropes such as AI as the ultimate solution to all problems yet at the same time the ultimate threat to humanity—and the reduction of the individual to data and computation—ignore how outcomes depend on the interaction between AI and social choices

In processes where decisions—both technical and social—about AI are made, different groups are situated unequally in power and awareness.[201] Excluding the voices of the people and groups most affected by AI has ramifications for how technologies are designed, deployed, used and regulated. Attitudes towards and approaches to understanding AI are not the same around the world. Tropes such as AI as the ultimate solution to all problems yet at the same time the ultimate threat to humanity—and the reduction of the individual to data and computation—ignore how outcomes depend on the interaction between AI and social choices.[202] It is thus imperative to develop a better understanding of the diversity of views about what AI is and its role in society and human development should be across cultures, extending beyond WEIRD (western, educated, industrialized, rich and democratic) countries.[203] Expanding people's agency is thus pertinent both to safeguard choices and freedoms and to ensure that AI technologies are useful for everyone everywhere to live lives they value and have reason to value.

Rooting the future of AI in social contexts

Dominant narratives tend to propagate claims about AI (or technology) as inherently emancipatory or oppressive. Those extreme views not only undermine human agency—they also neglect the role of social context in shaping the impact of AI. The term “AI” refers not to a specific technology but to a wide range of computational techniques, from logic-based automated decision systems to large language models based on deep neural networks.[204] Each technique comes with affordances and constraints and gives rise to different ethical, technical and social risks depending on its use case. For example, mobilizing AI and big data to convey local needs from a distance may risk perpetuating epistemic injustices and paternalistic practices in the humanitarian sector (Spotlight 4.3).[205] The same system may perform very differently for different people in different contexts. For example, generative AI would have very different outcomes depending on infrastructure, institutional capacity, regulations and social norms. Designing and deploying technologies often involve difficult tradeoffs—between accuracy and fairness, for instance—and must be evaluated on a case-by-case basis—with the participation of the people affected.[206] Narratives that propagate totalizing claims are unhelpful—and harm public discourse on the respective values, priorities, tradeoffs and consequences that may arise as a result of using AI in a particular context. They shift priorities from the more immediate impacts towards far-fetched future scenarios. And in doing so, they sow fear and may give rise to misinformed regulations.

Supplementing benchmarks of AI progress

More than three decades ago, the Human Development Report challenged the dominant narrative in development that focused exclusively on income to assess the progress of economies and societies. It did so by introducing the human development approach —a novel framework for evaluating and advancing human wellbeing and agency.[207] Indeed, one of the greatest achievements of the Human Development Report has been to promote greater acceptance of the fact that monetary measures such as gross domestic product per capita are inadequate proxies of development. Its framework laid the foundations for alternative metrics of human wellbeing, particularly the Human Development Index—which remains widely used. Subsequent Human Development Reports have revised and refined the metrics and developed new ones to capture other issues relevant to human development. A human development lens can help unearth the limitations of current metrics and inspire alternative metrics for evaluating the performance of AI in enhancing people's capabilities and agency.

AI benchmarks are combinations of datasets and metrics that represent specific tasks and are used to evaluate and compare the performance of AI systems.[208] The primary objective of many of these benchmarks is to measure the technical capabilities or performance of AI systems.[209] These benchmarks have been found to often fall short in measuring AI capabilities.[210] They rarely measure what they claim to measure,[211] can be easily gamed[212] and are sometimes impractical for real-world uses.[213] For example, benchmarks consisting of professional exams such as the bar exam "emphasize the wrong thing" and "overemphasize precisely the thing that language models are good at" and are thus unreliable measures of things such as legal skill.[214] Performance on the bar exam does not tell us anything about the performance of these models on real-world tasks.[215] Nonetheless, benchmarks have been useful in identifying social harms.[216] Quantitative measurements such as Correctional Offender Management Profiling for Alternative Sanctions[217] and Gender Shades[218] have set in motion some of the most influential changes in AI systems and are indispensable for assessing progress.[219]

Still, a more fundamental gap persists. Improving scores on a benchmark does not mean that an AI system would expand human development. That is, it does not reveal whether the system would enable people to achieve functionings that they have reason to value or would erode the space for exercising valued choices. As this and other chapters in this Report have demonstrated, AI can either enhance freedoms and opportunities for people or diminish their choices and agency. The direction it will go is contingent on the way it is designed and deployed and on whether appropriate policies and institutional mechanisms are put in place. Carefully curated benchmarks grounded in the human development approach can bolster action on these fronts.

> "The direction it will go is contingent on the way it is designed and deployed and on whether appropriate policies and institutional mechanisms are put in place. Carefully curated benchmarks grounded in the human development approach can bolster action on these fronts

Recently, concerns about the potential societal harms of AI systems have resulted in the development and adoption of specific benchmarks to assess the risks posed by such systems.[220] For example, the MLCommons AI Safety benchmark measures the safety of large language models by assessing their responses to prompts across multiple categories of impacts, including child sexual exploitation and suicide and self-harm.[221] But these evaluations focus mostly on the AI model itself. By contrast, impacts manifest in complex interactions between the model and social factors—comprising individuals and broader systemic factors.[222]

More generally, capabilities and risks are hardly attributes of models alone. They emerge from complex interactions among models, people, organizations and social and political systems. This is why existing approaches to evaluating AI systems are insufficient, especially when it comes to evaluating their societal impact.[223] Many of the concerning issues that have garnered attention—notably misinformation and bias—are not a property of the model alone. Rather, they are a joint property of the model and of a population of users who interact with a model in a particular way through a certain distribution of queries.[224] Unfortunately, data about these interactions are currently nonexistent.[225] This problem is compounded by the proprietary nature of many AI systems.[226] Therefore, research that focuses on empirically observing the interaction of people with large language models in different contexts and for different uses is critical to comprehensively assess capabilities and harms.

Ultimately, from a human development perspective evaluation of AI systems needs to be multidimensional, continuous and interdisciplinary. No single metric can capture the multifaceted impacts that AI systems have on people. Many of the identified harms of AI systems are latent concepts that cannot be captured in a single operationalization in their entirety.[227] And evaluation of AI systems inescapably involves choices and value judgements that must be made explicit and documented. In many instances different scores may have to be referred to in conjunction. For example, the Holistic Evaluation of Language Models benchmark adopts a multimetric approach (comprising accuracy, calibration, robustness, bias, fairness, toxicity and efficiency), measured across 16 core scenarios.[228] This ensures that tradeoffs are clearly exposed and that metrics beyond accuracy are not neglected. The development of metrics invariably has to be an ongoing process that captures emergent impacts as they surface and constantly explores new methodologies and data to measure the interactions among AI, people and society.

“Because the impact of AI systems spans economic, social, political and cultural dimensions, evaluating these systems should be a multidisciplinary exercise that incorporates different methodologies and makes space for diverse perspectives

Current benchmarks are designed only for the English language and based on western cultures.[229] Developing benchmarks for low-resource languages necessitates investment and effective collaboration among researchers, native speakers and communities. These benchmarks also focus on text-based AI systems—making them limited for other modalities such as images and audio.[230] Because the impact of AI systems spans economic, social, political and cultural dimensions, evaluating these systems should be a multidisciplinary exercise that incorporates different methodologies and makes space for diverse perspectives.

Narratives in economic decisionmaking

Attention to narratives as influential determinants of economic outcomes contrasts with traditional economic approaches fail to examine the role of narratives in major economic events.[1] Burgeoning work in narrative economics seeks to study the ways narratives spread and affect economic behaviour—including decisions as diverse as whether to make an investment or whether to have a child.[2] Economic decisions often hinge on the belief or disbelief of certain stories because stories can influence expectations, inspire confidence or instil fear in economic agents.[3]

Empirical work has sought to document the influence of narratives on economic behaviour. For instance, an open-ended survey of macroeconomic narratives of households and experts finds that household narratives are much more heterogenous than expert narratives and strongly shape their inflation expectations.[4] The media are an important source of these narratives.[5]

Of particular relevance is the role of narratives in decisionmaking under conditions marked by radical uncertainty.[6] In contexts marked by radical uncertainty, "people use narratives to make sense of the past, imagine the future, commit to action, and share these judgments and choices with others."[7] Conviction narrative theory asserts that "narratives arise from the interplay between individual cognition and the social environment, with [people] adopting a narrative that feels 'right' to explain the available data; using that narrative to imagine plausible futures; and affectively evaluating those imagined futures to make a choice."[8]

The role of narratives in a broad range of phenomena have been studied—notably prices of cryptocurrencies[9] and fertility decisions. Evidence indicates that narratives also carry substantial collateral effects on financial market expectations and economic decisionmaking.[10] In a similar vein both experimental and survey evidence have demonstrated the causal impact of narratives of the future on fertility intentions, whereby positive future narratives positively affect fertility intentions and negative narratives produce the opposite effect.[11] People use these narratives to project themselves into an actionable imagined future and make decisions that are somewhat independent of their actual economic situation.[12] For instance, in an experiment conducted during the Covid-19 pandemic, respondents were exposed to different scenarios regarding the expected length of the pandemic. The longer the expected duration, the lower their fertility intentions.[13]

In addition to their role in understanding the environment, focusing attention, predicting events and motivating action, narratives also play an important part in allocating social roles and identities, defining power relations and establishing social norms.[14] Indeed, narratives are strategically employed by political agents to achieve a certain purpose. Political agents discover identity and policy narratives that shift beliefs about how the world works or about identity to catalyse policy and institutional change in a certain direction in line with their interests.[15] Narratives shape social identities, as people generally make sense of their lives in terms of stories that are influenced by their relations with others and their environment.[16] Narratives also define power relations through their role in organizing perceptions around socially conferred characteristics such as expertise, legitimacy and social identification.[17] Moreover, in addition to their role in specifying norms of behaviour, narratives also supply principles of application rooted in particular social relationships.[18]

Shared narratives can support coordination. They usually propagate when they are appropriate to the context, are unforgettable and have popular appeal.[19] As such, ideas held collectively in a social network can become the coordinating device for a range of decisions in a similar way to the role of prices.[20] Narratives thereby set beliefs and inform action that carry important macroeconomic consequences. This opens the possibility for political leaders to reset narratives to change ideas about identities and norms in order to build social pressure towards support ing actions that are in the common interest.[21]

Two crucial insights emerge. First, paying attention to narratives can help in anticipating and preparing for economic events and in structuring institutions and policies. Second, reframing narratives can be a powerful way to drive policy and institutional change, precisely because of their role in setting beliefs and perceptions and in influencing both individual and collective behaviour.

NOTES

1. Shiller 2020; Akerlof and Snower 2016.
2. Shiller 2020.
3. Akerlof and Shiller 2010.
4. Andre and others 2024.
5. Guetto and others 2023.
6. Despite increased scholarly attention to narratives in economics, this term is used and defined in multiple ways. Specifically, three roles have been ascribed to narratives in economics: narratives as interpretive summaries of specific issues, narratives as a means of policy analysis and narratives as active drivers of economic decisions. See Roos and Reccius (2024) for an overview of the literature.
7. Johnson, Bilovich and Tuckett 2023, p. 2.
8. Johnson, Bilovich and Tuckett 2023, p. 1.
9. Azqueta-Gavaldón 2020.
10. Paugam, Stolowy and Gendron 2021.
11. Guetto and others 2023.
12. Guetto and others 2023.
13. Guetto, Bazzani and Vignoli 2022.
14. Akerlof and Snower 2016.
15. Mukand and Rodrik 2018.
16. Akerlof and Snower 2016.
17. Akerlof and Snower 2016.
18. Akerlof and Snower 2016.
19. Johnson, Bilovich and Tuckett 2023.
20. Collier and Tuckett 2021.
21. Collier and Tuckett 2021.

SPOTLIGHT 4.2

Caring through digital platforms

Digital labour platforms can increase the labour force participation of women, particularly from marginalized groups, by facilitating access to labour markets. This promise is often based on the flexibility afforded by these digital platforms for women to balance paid work with household responsibilities.[1] A burgeoning platform care economy for domestic, cleaning and care-related work has emerged around the globe. Such platforms act as intermediaries for allocating and assigning care work. The platforms have been viewed as solutions to the demand- and supply-side challenges in care. These novel technologies offer the possibility of reorganizing the demand and supply of work to foster flexibility and personalization by addressing information asymmetries between workers and clients. Platform work by its very nature reduces barriers to entry because it involves an automated signup process, allows for flexible work schedules and permits both platforms and workers to make fewer commitments.[2]

Participation in the platform does not inevitably bring about better working conditions for women.[3] Platform work attracts workers who experience precarity and vulnerability on account of gender, race, immigration status, caste and ethnicity.[4] Therefore, while platforms offer opportunities, they can also exploit workers who depend on them disproportionately and have fewer avenues to organize and challenge unfair working conditions.[5] This is partly because of information asymmetries between platforms and workers. The workers on these platforms—mostly poor women—often toil under exploitative conditions marked by long and irregular hours, wage precarity, negative impacts of algorithmic management practices and harassment.[6] The flexibility propagated by the platform can be a myth because women often have to work longer hours and at odd times of the day.

Flexibility frequently becomes a tool for legitimizing double shifts for women, who have to juggle paid and domestic work. For instance, the availability of work and wages on these platforms is dictated by a rating system. While workers are under constant pressure from this system, they may be unable to rate customers or flag abusive customers.[7] For instance, women on South Africa's SweepSouth platform are required to provide quality cleaning services, as this affects their ratings and future access to work. But workers are rarely given sufficient information about how big the house is.[8] In addition, workers who cancel or refuse a task, or resist doing extra work that was not initially specified in their booking, can be penalized.[9] Further, workers can have their accounts deactivated or suspended without any recourse if their ratings fall below a particular threshold or if they repeatedly refuse bookings.[10]

In certain countries wages on these platforms are higher than those for offline work. But work on these platforms is inconsistent, and the potential for higher earnings could be offset by the time spent looking for suitable opportunities and commuting between locations.[11] Platform companies also charge high commission rates from workers.[12] Thus, platforms set the conditions of work and wages, interface between workers and employers, collect data about both care workers and care recipients and take a substantial proportion of workers' earnings in the form of commissions and deposits.[13]

Misclassifying workers on platforms as self-employed, independent contractors or partners may allow platforms to circumvent labour laws and regulations, further marginalizing domestic workers, who are often migrant women.[14] The platforms fail to serve the needs of women, who constitute a majority of their workers, and to protect and promote their safety. Sexual harassment at work is a major concern for care and domestic workers because they work in confined environments in their client's homes.[15] Still, technological features and policies to ensure the safety and security of care workers are usually missing from many of these platforms.[16]

Digital platforms by and large cater to the needs of time-poor rich households that can afford to pay for care while relying on an underpaid feminized workforce whose care needs remain unmet.[17] Thus, it makes care available for some, while precluding it for others.[18] For instance, women working on care platforms in Thailand struggle to balance the demands of platform work with their family responsibilities. These women often have to rely on other family members such as grandparents to take care of their children.[19] In fact, women with caregiving responsibilities are often penalized on these platforms due to their inability to take up work at short notice or at odd hours.[20]

Even so, workers on these platforms have exercised their agency to resist the working conditions on these platforms. Digital communication tools facilitate new modes of connecting workers and activists across distances. Carers who work in isolation in private homes have long been deemed unorganizable.[21] But digital communication tools have bolstered their ability to build and maintain grassroots movements and raise public awareness for their concerns. It was exactly this opportunity that the National Domestic Workers Alliance—a leading voice for the respect and dignity of domestic workers in the United States—leveraged to organize workers on the Handi platform.[22] Through organizing efforts and negotiations over two years, the workers won an agreement that includes minimum wages, paid time off, occupational accidents insurance and a formal process to address workplace concerns. Likewise, domestic workers on India's Urban Company and South Africa's SweepSouth platforms used Facebook and WhatsApp to share information and opportunities, request assistance, vent their frustrations and reclaim a sense of dignity.[23]

In some instances these forms of coordinated individual resistance have coalesced into collective action. Digital technologies become important tools for these workers to find each other, discover communities and solidarities and articulate shared experiences. These efforts culminated in the largest nationwide labour action by female gig workers working with Urban Company in India to resist algorithmic management practices and account deactivations. Women have drawn on digital technologies, as well as informal kin networks, to coordinate protest actions against digital labour platforms, with the support of the established trade union movement.[24]

In some countries female platform workers have developed cooperatives. These workers use app-based technologies to organize while preserving fair compensation for workers and promoting job security. For example, Equal Care in the United Kingdom[25] and Up & Go in New York[26] were both founded by women to shift power to the hands of platform workers. The expansion of women-owned platform cooperatives constitutes an opportunity to advance a more inclusive reorganization of work in the digital economy. Still, platform cooperatives struggle to expand and survive amid stiff competition from more powerful digital platforms.[27] So, public policies that support women-owned platform cooperatives are key to bolstering alternative ways of leveraging digital platform technologies to contribute to quality care and decent work.

Even digital labour platforms could improve working conditions—through, for example, offering more than minimum wage and regulating work hours.[28] State support is paramount, including on research and innovation, public services and infrastructure, and social protection systems. In reality, policy interventions and institutional responses have to account for context, recognize structural norms and imbalances in the care sector and reflect the voices of those historically marginalized and excluded from technological advances.

NOTES

1. Anwar 2022.
2. Kalla 2022; Tandon and Sekharan 2022.
3. Rani and others 2022.
4. Rodríguez-Modroño, Agenjo-Calderón and López-Igual 2022; Ticona and Mateescu 2018.
5. Rodríguez-Modroño, Agenjo-Calderón and López-Igual 2022.
6. Hussein 2022; Rodríguez-Modroño, Agenjo-Calderón and López-Igual 2022.
7. Tandon and Rathi 2021.
8. Kalla 2022; Sibiya and du Toit 2022.
9. Sibiya and du Toit 2022; Tandon and Sekharan 2022.
10. Kalla 2022; Sibiya and du Toit 2022.
11. Tandon and Rathi 2021.
12. Dhar and Thuppilikkat 2022; Tandon and Sekharan 2022.
13. UN Women 2023.
14. Kalla 2022; Rodríguez-Modroño, Agenjo-Calderón and López-Igual 2022; Sibiya and du Toit 2022.
15. Dhar and Thuppilikkat 2022.
16. Athreya 2021.
17. Fraser 2016.
18. Green and Lawson 2011.
19. Just Economy and Labor Institute 2022.
20. Just Economy and Labor Institute 2022.
21. Hobden 2015.
22. National Domestic Workers Alliance n.d.; Zundl and Rodgers 2021.
23. Dhar and Thuppilikkat 2022; Sibiya and du Toit 2022.
24. Dhar and Thuppilikkat 2022.
25. https://www.equalcare.coop/.
26. https://www.upandgo.coop/.
27. Salvagni, Grohmann and Matos 2022.
28. Sibiya and du Toit 2022.

SPOTLIGHT 4.3

Mobilizing big data artificial intelligence for localization: The risks of reproducing unequal power hierarchies

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The convergence of technical advances in big data, artificial intelligence (AI) and algorithmic complexity, along with the growing accessibility and affordability of services integrating these technologies, is transforming the humanitarian sector. Big data and AI are introduced to promote professionalization through standardization, speed and perceived objectivity or to strengthen empowerment by improving accessibility, transparency and broadening the stakeholder base.[1] Over time, however, research has increasingly shown how this trend toward "digital humanitarianism" has also enabled remote management techniques that sometimes sideline concerns about data regulation and privacy protection. It has raised questions about the dominance of private corporations in shaping the use and outcomes of "extractive" data practices and systems that are designed primarily with commercial objectives in mind.[2] Recent developments reveal a merging of datafication with a central priority in contemporary humanitarian affairs: localization. Epitomized in political discussions around the Grand Bargain agreement, launched at the World Humanitarian Summit in Istanbul in 2016, localization advocates shifting humanitarian responsibilities from international agencies to actors who are more closely embedded in affected communities.

What happens when humanitarian actors mobilize AI as a shortcut to localization? Are these emerging technologies able to construe accurate depictions of local needs and demands? And what are the effects of these developments for representation, inclusion, and the wider ambitions of the localization agenda?

Datafied localization

Localization aims to address the critique that humanitarian efforts have been driven predominantly by Western responses to conflicts and disasters, often sidelining local actors who historically received less than 0.3 percent of formal system funding.[3] As part of the 2016 Grand Bargain, this political agenda seeks to empower local communities and local humanitarian organizations by increasing funding, capacity building, fostering equitable partnerships and establishing inclusive coordination platforms.

The backdrop to the localization agenda is a growing body of evidence showing that local participation and leadership enhance global response effectiveness.[4] The premise is that proximity to crisis leads to faster and more contextually relevant responses, but this aim is hindered by an entrenched hierarchy between international (often Western) humanitarian actors and locals—a category that itself has been criticized for being reductionist. Despite a rhetoric of partnership, equality and commitment to bottom-up decisionmaking, it is well documented that humanitarian collaborations frequently result in hierarchized relationships where local nongovernmental organizations act as subcontractors with limited decisionmaking power.[5] This has underscored a key tension between inclusion and transformation.[6]

In this context of localization, AI and data-driven tools are increasingly deployed to create a sense of "proximity" to targeted populations. By drawing on a plethora of data sources, including satellite imagery, social media feeds, local analytical gig work and mobile communication patterns, big data is deployed to generate real-time insights into the evolving dynamics of particular crises. The integration of big data spans numerous humanitarian efforts, from personalized healthcare, real-time environmental monitoring and crisis mapping to the registration of biometrical datapoints aimed at identifying and tracking individuals or groups. These data-driven approaches influence risk assessments, resource allocations and decisionmaking in crisis response. In particular, the extraction and utilization of big data under the guise of localization stress three main concerns: fabricating context, rendering representation at a distance and reproducing power imbalances.

Fabricating context

The localization agenda advocates for a paradigm shift towards empowering local actors, assuming that proximity enables quicker and more efficient responses to humanitarian crises. But using AI and big data tools to make human suffering commensurable across borders sometimes rests on an individualist or universalist ontology of needs, which risks reinforcing unequal power hierarchies within humanitarianism.

While big data can seem void of context, all data are. local, embedded within sociotechnical, cultural and organizational contexts.[7] As such, the representation of a humanitarian crisis from a distance through big data risks resulting in abstracted representations of people and social phenomena. This constitutes a fabrication of context, signifying a shift from viewing big data as contextless to seeing it as offering an image of an empirical reality crafted from real-time microdata, rich in detail but detached from specific geographical locations. These approximations then inform recommendations for action across countries or communities that may turn out to be generalized but have localized consequences.

In this process context is reduced to an assortment of data points algorithmically assembled, producing a specific perspective on reality. While big data is often presented as empowering, we must remember that digital tools are not universally used, especially in times of crisis. Such approaches risk overlooking that global social media platforms vary in their use across contexts, and words or phrases carry distinct meanings depending on their cultural or situational setting.[8] Despite the Western-centric perspective that often accompanies AI trained predominantly on English language data, online data collection is still portrayed as less biased than traditional research methods. But data need to be interpreted to become knowledge, and the diversity of local cultures, expressions and media use renders the adaptation of universal principles to local contexts exclusionary. As a result, the data-driven aggregated classifications suggested by these new AI tools may produce generalizations that overlook marginalized voices. This concern is particularly substantial given the growing recognition that comprehending events, actions and crises in their broader cultural, sociopolitical and environmental contexts enhances the cultural appropriateness and sustainability of response and recovery efforts.

Rendering representation at a distance

Representation is central to humanitarian action because it ensures the inclusion of diverse voices and perspectives in decisionmaking. Local representation, in particular, fosters accountability and legitimacy, as it reflects the needs and priorities of affected communities. This is integrated into the localization agenda, which seeks to transfer responsibilities, capacities and resources to local actors. Beyond efficient disaster management it emphasizes fair representation as a normative ideal, addressing broader discussions on rights and justice.

Representation often begins from the point of who is rendered visible, as invisibility through lack of documentation and data remains a key concern at the intersection of datafication and inequality. But representation also confronts us with the question of who and what remain local?

The concept of local is inherently complex, with diverse definitions reflecting the lack of consensus in the humanitarian community.[9] One challenge stems from the relativity of the concept of local, as it is intertwined with spatio-geographical, social and identity distinctions in crisis-affected countries and contexts. A static understanding of local as tied to a specific place or locale struggles to encompass diaspora, migrants and internally displaced people, sparking calls for a critical approach to localism. This perspective views the local as highly contextual and relational, focusing on the processes through which the label is constructed.[10]

As AI-driven representations of local realities emerge, defining local becomes even more pertinent. How are the boundaries of local defined and maintained in these recontextualized versions? The limitations of proximity as a defining factor for localism become apparent, as individuals engaged in gig work may be physically close to humanitarian situations without truly being part of them or understanding those affected. Rather, this seems to align with descriptions of the humanitarian field as a quasi-market in which beneficiaries become "the means to an end."[11]

As already touched on, AI-enabled services of localization accentuate the digital divide across access, use and outcomes, especially for companies that depend on social media for construing their geometries of local needs and interests.

Many current services rely on convenience sampling, a methodology criticized for biases resulting from underrepresentation. When convenience (that is, access) becomes the sole criterion for inclusion, there is no mechanism to screen for sampling biases, raising doubts about both internal and external validity. When informants are approached as users and gig workers in a market, biases often favour those with some resources to begin with. Thus, the integration of big data for localization not only bypasses direct engagement with local actors or communities but also enables humanitarian organizations to continue speaking on their behalf. In sum, emphasizing big data–driven localization risks blurring the distinction between local elite perspectives and a reified interpretation of local as a fixed space whose concerns can be readily extracted, transported and interpreted across distances.

Reproducing power imbalances

Localization aims to reconfigure the humanitarian system by bolstering local decisionmaking power and agency to challenge entrenched hierarchies. Framed as a means to enhance the reach, effectiveness and accountability of humanitarian action, localization ideally serves as a decolonial or social justice endeavour.[12] Yet current evidence indicates that data practices may take on extractive forms.[13] This raises concerns that integrating big data into localization efforts risks perpetuating power imbalances by reducing local communities to mere data providers or by bypassing local humanitarian organizations.

The ongoing digital transformation of humanitarianism and the shift towards localization have prompted discussions about the skillsets frontline humanitarians need to implement technology-driven solutions effectively.[14] This transformation is envisioned as a way to mitigate the consequences of the growing gap between the complexity of digital technologies deployed by international humanitarian organizations and the level of digital literacy among local partners—a gap further exacerbated by the prevalence of short-term funding structures under which local organizations often operate.[15] Although, datafied localization can enhance technology's reach by tailoring it to local conditions, it can also facilitate remote management techniques, maintaining local organizations in contractual relationships with international donors and potentially reinforcing existing power imbalances.[16]

Remote management enabled by datafied localization could exacerbate unequal power dynamics by shifting risks onto local partners[17] and introducing new issues related to organizational accountability, risk management and forms of ignorance.[18] While local partners may undergo digital literacy training, it often concentrates on specific tools and applications rather than building their overall capacity to use digital technology and data effectively and independently.

Introducting technology can enable more efficient extraction and commercialization of data by entities located predominantly in developed countries. Herein, locals are reduced to data producers through gig work, thereby becoming part of territories from which data can be extracted and exploited from the distance. In these relationships employer responsibility becomes fragmented across long supply chains, with ultimate control lying solely with the client.[19]

Conclusion

This discussion shows how mobilizing AI and big data to convey local needs from a distance—what can be called datafied localization—risks perpetuating epistemic injustices and paternalistic practices in the humanitarian sector, if not pursued reflexively. Big data does not remove questions of contextualization, representation and power hierarchies. Instead, questions of what data are, who data represent and what data show remain a considerable structuring force for delivering humanitarian support. Current attempts at shortcutting localization stress the need for critical discussions of distance and proximity, as well as their intersections with emerging technologies. While localization through AI datafication may ostensibly be seen as a way to acknowledge local voices, a closer look shows that the modes in which it is currently conceptualized risk reproducing power asymmetries in ways that run counter to the core intentions of localization.

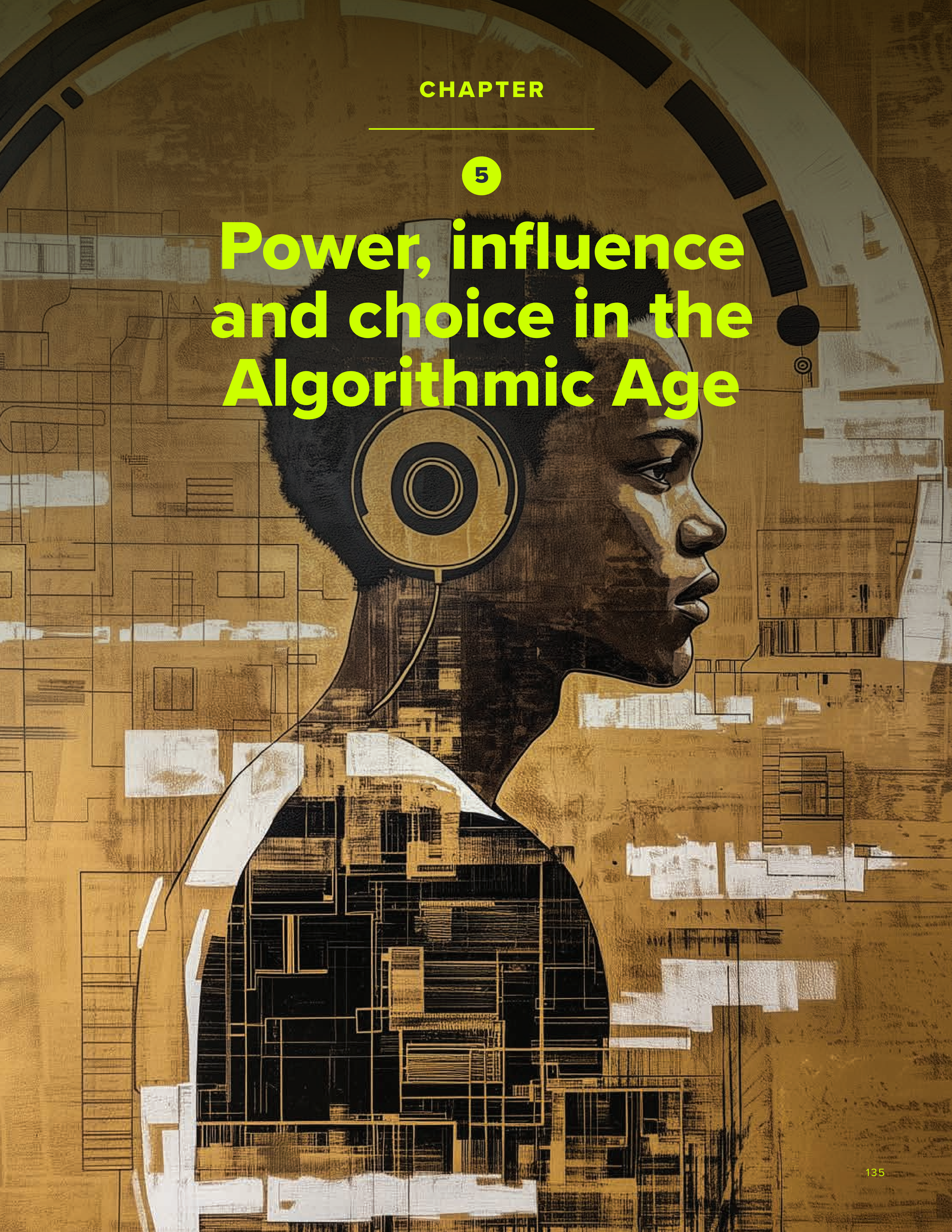
NOTES

1. Mulder and others. 2016; Raymond and Al Achkar 2016.
2. Duffield 2016; Fejerskov, Clausen and Seddig 2024; Sadowski 2019.
3. Australian Red Cross 2017; Poole 2018; Seldon, Abidoye and Metcalf 2020.
4. Fox 2020; Honig 2018; Khoury and Scott 2024.
5. ALNAP 2022; Kraft and Smith 2019; Schenkenberg and others 2020.
6. Barnett 2018; Fast and Bennett 2020; Melis and Apthorpe 2020; Pailey 2020; Pincock, Betts and Easton-Calabria 2021.
7. McCosker and others. 2022.
8. Costa 2018.
9. Barbelet and others. 2021; Wall and Hedlund 2016.
10. Roepstorff 2020.
11. Krause 2014.
12. Roepstorff 2020.
13. Sandvik 2023.
14. Frost, Khan and Vinck 2022.
15. Ghorkhmazyan 2022.
16. Elkahlout and Elgibali 2020. The authors refer to "remotely managed localized humanitarian action" and use the case of the Syrian Arab Republic to establish that remote management can facilitate localization, although with ethical and legal risks for local nongovernmental organizations.
17. Duclos and others 2019.
18. Fejerskov, Clausen and Seddig 2024.
19. Mejias and Couldry 2024.

CHAPTER

5

Power, influence and choice in the Algorithmic Age



CHAPTER 5

Power, influence and choice in the Algorithmic Age

Much of this Report focuses on the demand side of artificial intelligence (AI). This chapter shifts the lens to the supply side, asking what kinds of AI tools are developed, for what purposes and by whom.

The chapter examines "power over" people: how AI producers and sometimes AI itself have the ability to affect people's prospects (in positive and negative ways), alter their options (the choices they can exercise) or influence their beliefs and preferences (including what they value and have reason to value).

Much of the Report's analysis thus far has focused on artificial intelligence's (AI) potential to give, or constrain, people's power to do things. For example, chapter 1 explores the potential of large language models to enable people currently excluded from accessing advanced expertise and know-how to have both in greater reach. This chapter moves from a discussion of "power to" to an examination of how AI has and shapes "power over" people.[1] Having "power over" means than an agent is able to affect others' prospects (in positive and negative ways), alter their options (the choices they can exercise) or influence their beliefs and preferences (including what they value and have reason to value).[2] Both the agent with power and those whom power is exercised over have always been people.

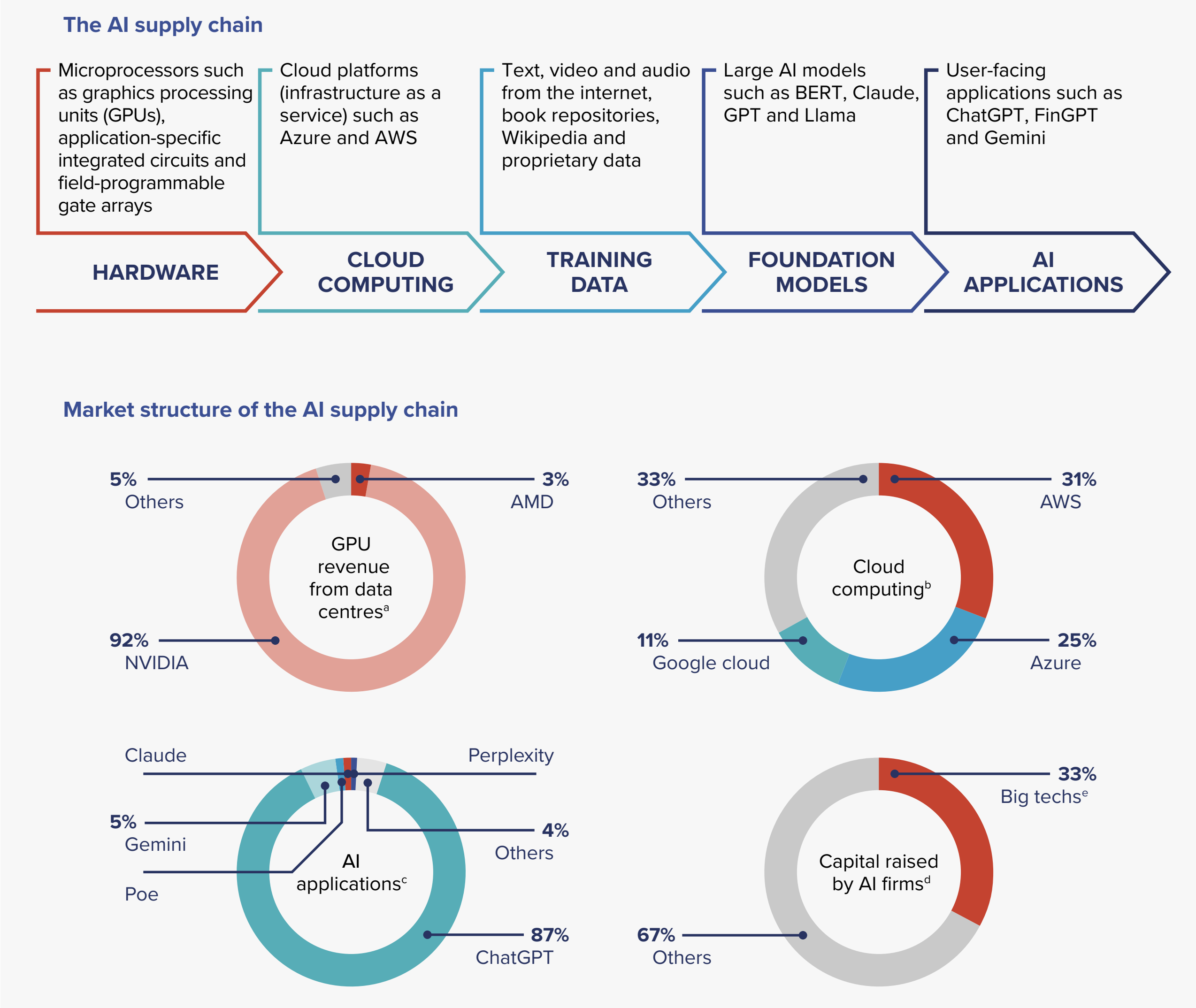
But AI's agentic characteristics (chapter 2) suggest that some AI models have agential power over people.[3] In classical programming digital tools were simply executing a set of preprogrammed rules, and thus power could be mediated by those tools but was ultimately exercised by the programmer. In contrast, AI models often operate beyond the effective control of the people who design and deploy them. This presents a historically novel means of exercising power, adding to the many ways power has been exercised over time—through laws, parental voices, regulatory incentives, social norms and more.[4] It also gives those designing and deploying AI, on the supply side, new means (intended or unintended) of exercising power over people. That is the subject of this chapter.

Many are the possible threads to follow in this examination. An obvious one that has generated much public and policy interest relates to the market structure of the AI supply chain. One breakdown of this supply chain includes five components: computing hardware, cloud computing infrastructure, data used to train AI models, foundational models (such as GPT)[5] and consumer-facing applications (such as ChatGPT and the hundreds of thousands of applications that run on GPT and other foundational models; top panel of figure 5.1). A few firms account for large shares of the market, particularly in hardware and AI applications (bottom panel of figure 5.1).[6] Big technology companies (Big Tech) are present to varying degrees across the supply chain in different ways (sometimes dominating markets, as in cloud computing; in other cases investing in AI companies as shareholders). Market concentration raises several policy concerns,[7] including the potential to limit consumer choice (perhaps through consumer lock-ins), restrict entry by smaller and newer firms, shape the direction of innovation away from socially desirable outcomes,[8] create single points of failure that harm cybersecurity and operational resilience of critical infrastructure and make financial stability more vulnerable to procyclical responses during financial stress.[9]

> "Market concentration raises several policy concerns, including the potential to limit consumer choice (perhaps through consumer lock-ins), restrict entry by smaller and newer firms, shape the direction of innovation away from socially desirable outcomes, create single points of failure that harm cybersecurity

At the same time the market for frontier foundation models is dynamic, fluid and characterized by intense competition among dozens of AI labs. Several open-source models have been deployed.[10] Although open-source models may be more vulnerable to misuse and cyberattacks and their producers may sell complementary services in exclusive bundles that may limit competition,[11] they offer more flexibility and potential for customization that can enhance competition and innovation.[12] The fluidity of the market implies that things can change quickly—for example, if one model acquires capabilities vastly superior and out of reach of others or if first-mover advantages entrench one supplier, as in the dominance of ChatGPT up to 2024—in both ways the market can tip from decentralized to heavily concentrated. Concentration can also happen through vertical integration, with a few firms consolidating activities upstream, ranging from data to chips, and downstream, using their existing market reach to get to consumers.[13] Concerns over market concentration are typically addressed by competition policy, but concentration in the AI supply chain raises new issues potentially beyond the reach of competition policy. For example, the digital economy, and AI in particular, brings new challenges in interpreting and applying competition policies and determining which jurisdictions to do so in, given the international reach of several AI applications.[14] Of course, the economic impacts of AI extend beyond market structure, but the speed of change and vast scope of AI are creating different regulatory approaches across jurisdictions to deal with the many challenges.[15]

Figure 5.1 The market structure of the artificial intelligence (AI) supply chain is concentrated



a. Based on global revenue of graphics processing unit (GPU) producers for GPUs used in data centres in 2023.
b. Based on global cloud computing revenue for the first quarter of 2024.
c. Based on monthly visits data.
d. Based on total capital invested in 2023 in firms active in AI and machine learning, as collected by PitchBook Data Inc.
e. Corresponds to Alibaba Cloud Computing, Alibaba Group, Alphabet, Amazon Industrial Innovation Fund, Amazon Web Services, Amazon, Apple, Google Cloud Platform, Google for Startups, Microsoft, Tencent Cloud, Tencent Cloud Native Accelerator and Tencent Holdings.
Source: Gambacorta and Shreeti 2025.

Rather than focus on the market structure of the AI supply chain alone, this chapter starts with a framework for interpreting how today's AI is exercising power over people and for considering what to bear in mind as the AI supply chain continues to change and AI applications evolve and diffuse.

Chapter 1 emphasizes that when AI outputs result in outcomes with high stakes, the need for human evaluation should be carefully considered. Stakes also matter to assess whether "power over" warrants concern and examination. That assessment depends on individual and public reasoning, with three elements to help determine whether the stakes are high: concentration, degree and scope (table 5.1).[16] Building on the intuition from market concentration, the first element is whether power is concentrated, not only in a market sense but also with a broader meaning: the fewer the people exercising power over a larger number, the more reason there is to consider the stakes high. A niche AI application in a narrow economic sector has lower stakes than

Table 5.1 When do we confront high stakes? When "power over" is concentrated and impacts deeply or across many dimensions of people's lives

Element	Description
Concentration	The fewer the people exercising power over a larger number, the higher the stakes
Degree	The greater the impact on people's lives (property, freedom, life), the higher the stakes
Scope	The more dimensions of people's lives affected (scope), the higher the stakes

Source: Human Development Report Office.

a firm making decisions on algorithms governing interactions in digital platforms that billions of people use. The second element is the degree to which people are affected. The degree is higher when the impact touches on someone's property or, in more extreme cases, freedom or life (chapter 1). Even more mundane uses of AI, such as in automatic contracts in which lack of payment for a car loan blocks access to the car, may imply a greater impact than how noncompliance would be dealt with in the absence of AI.[17] The impact can also be high if many people are affected in ways that are not directly very consequential at the individual level but are substantial for a large group or society as a whole, as in political deliberation.[18] The third element is the scope of impact, with the stakes higher when power is exercised over several dimensions of people's lives.

When one or a combination of these elements implies high stakes, we should examine three aspects roughly linked to what power does, how it is exercised and by whom.[19] What power does relates to the substantive outcomes associated with designing and deploying AI. Understandably, this has been the focus of attention given AI's novelty and potential to affect outcomes for people and societies across many facets of life. There are multiple, often interrelated, strands of work. AI safety focuses on avoiding accidental misuse or systemic risks.[20] It also extends to concerns over existential risk.[21] AI ethics has often been inspired by the "do no harm" duty of medicine but has also considered concerns ranging from upholding human rights, protecting privacy and addressing biases.[22] More ambitious approaches seek to align AI with human values so that AI not only avoids harms but is also used for good.[23]

But even if it were possible to exercise power over people with AI systems that result in desirable outcomes, people also care about how that power is exercised—or what is described in political deliberation as procedural legitimacy.[24] Fields such as trustworthy AI or responsible AI attend in part to this aspect.[25] Procedural legitimacy includes such aspects as equal treatment under a source of power (say, the law) as well as due process standards—for example, contesting how a decision was made. AI is often opaque and does things beyond what it was designed for, making it hard or impossible to meet these standards: one reason AI transparency and explainability matter.[26] The higher the stakes, the more people care about the explainability of AI,[27] including in medical applications, where accuracy is often not seen as enough.[28] Finally, who makes the decision matters, particularly when the decision has implications for many people who may not have had the chance to influence it. Moreover, AI itself, in a sense, exercising power over people raises new questions beyond considering people who design and deploy AI.[29]

So, even though whether artefacts "have politics" is a longstanding debate in the history and culture of technology,[30] AI-powered algorithms do wield power not only to but also over.[31] In the context of today's AI-powered transformation, two forms stand out for human development:

- First is the unique and pervasive power that algorithms have in mediating our social interactions and social choices. The 2023/2024 Human Development Report found that nearly 70 percent of the population feels they do not have a say in governmental decisions.[32] This highlights a high baseline level of disempowerment among the public. A critical question is thus how this will evolve with AI's ability to shape "power over."
- Second is the outsized power that a few people, companies and countries have in designing and deploying AI. This has consequences for people's choices and freedoms—how they are shaped by a powerful new technology over which many have, so far, had precious little say.[33]

Algorithms shape social choices and power

We live in a novel social reality where algorithms (many of them AI-based) mediate many of our social relations and shape much of our engagement with the world. Whether through social media, search engines, online shopping or digital communication tools, algorithmic intermediaries are reshaping the landscape of human-to-human interactions, defining the context and boundaries within which people engage.[34]

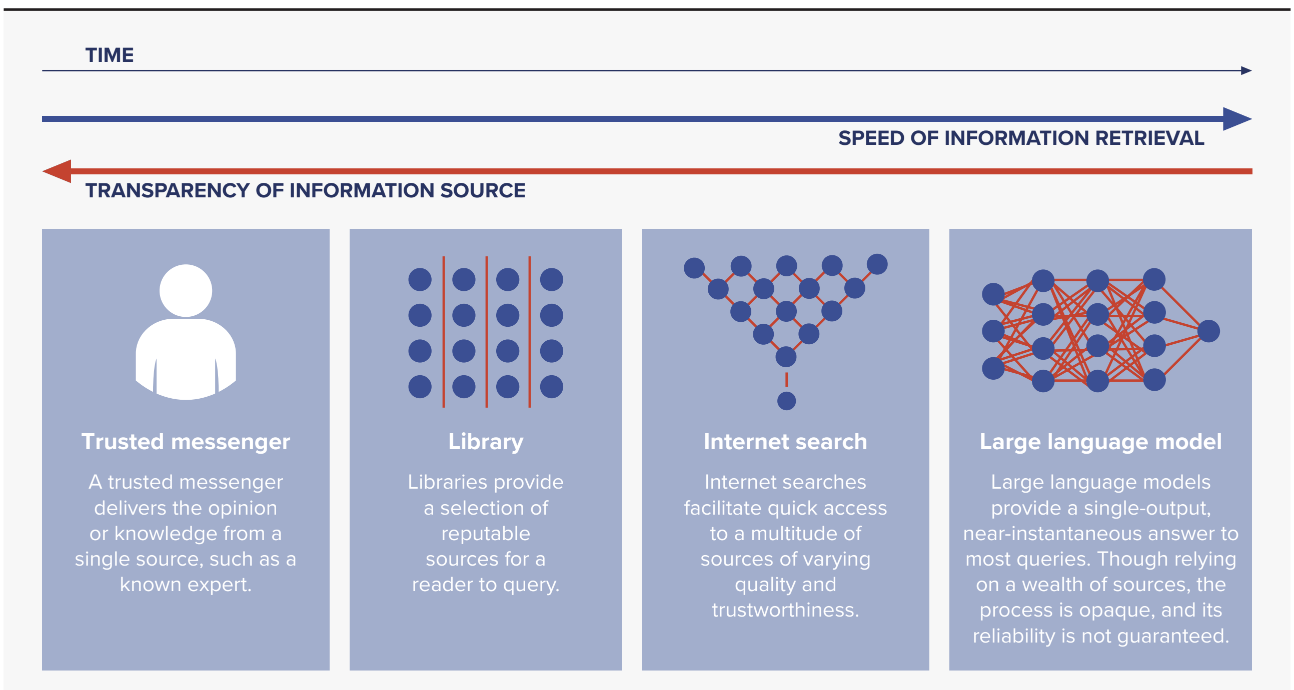
Philosopher Seth Lazar calls this the algorithmic city—articulating how computational machines have revolutionized interactions between people.[35] In this shifting landscape new forms of power are taking shape.[36] Think about how algorithms have fundamentally altered the way we access and engage with information.[37] We have attained extraordinary speed in retrieving information; however, the reliability of that information, its source and authenticity are often opaque (figure 5.2).[38] Consider the trust we place in the ranking of web search results, and increasingly also in searches using generative AI, despite having little insight into the algorithms that determine their order.[39] Or reflect on the way algorithms in social media platforms shape narratives and distribute people's attention, as shown below.[40] Or think about how generative AI—trained using around 90 percent English materials[41]—shapes our views and opinions about the world.

Evolving power dynamics

In this sense algorithmic intermediaries are subtly shaping the fabric of society and influencing human relations and behaviour in ways both profound and unseen. To examine in detail how AI "power over" is manifested, take the recommender systems widely deployed in web search and digital platforms. This type of AI is one of the most consequential ways that AI algorithms mediate and influence human relations, interacting with social, political and economic processes, shaped by and shaping economic incentives, regulations and social norms (figure 5.3). Recommender systems shape how we navigate the infinite amount of information online, find the things we want to buy, connect with friends or follow people and events.

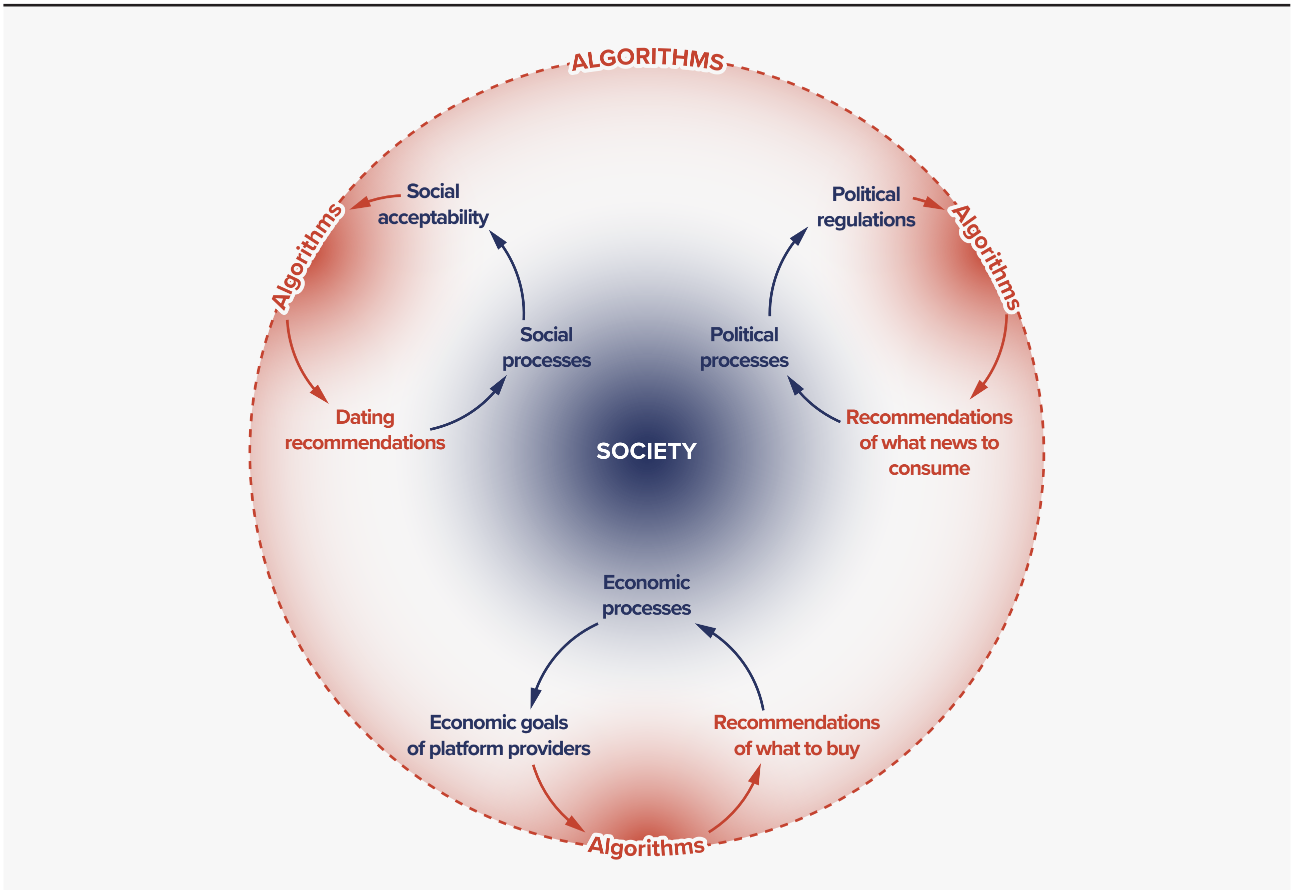
In 1971 computer scientist Herbert Simon argued that in an information-rich world, attention becomes a scarce resource.[42] He identified the scarcity of attention in a world with abundant information as a challenge in digital societies that requires filtering information to ensure that people can access what is most relevant to them.[43] The information throughput of a human is estimated to be 10 bits per second.[44] One

Figure 5.2 Artificial intelligence transforming the way people retrieve information



Source: Burton and others 2024.

Figure 5.3 **Recommender algorithms show how artificial intelligence is shaping social, economic and political processes**



Source: Wagner and others 2021.

way people overcome this limitation is by working together,[45] but if a single human were to go through all the content of the internet today, it could take over half a billion years.[46] As the amount of information available in our increasingly digital world continues to expand, recommender algorithms channel our attention, seeking what is relevant to each person. A core challenge of leveraging the internet for human development is that the information people use to promote their own agency and improve their capabilities far exceeds what anyone can reasonably consume. To overcome this limitation, algorithmic tools to search and filter information have come to define the modern internet. From early web searches and later social media feeds to modern chatbots, our experience of the internet is filtered through some form of algorithm, often AI-based recommender systems.

That is also the case for social media,[47] which has 5.24 billion users, or almost two-thirds of the global population.[48] The typical model of recommender algorithms in social media is fuelled by the behavioural record of users, with recommender algorithms optimized to keep users engaged on the platform.[49] Data to enable these algorithms to make recommendations come from what people do online, which has raised concerns about privacy violations, potential exploitation of people and manipulation of beliefs and behaviours.[50] From a human development perspective these systems may also curtail human agency by making choices on our behalf over what we want to see—choices that may better reflect industry incentives than our own agency (box 5.1).[51]

The case of recommender systems allows for a more concrete examination of the ways "power over" is exercised. Recommender systems do more than just regulate information flows—they shape the very conditions in which people interact online. Think about how the law operates: it sets boundaries by prohibiting

Box 5.1 Recommendations in digital platforms and human development: Artificial intelligence as part of the problem, part of the solution?

Artificial intelligence (AI) is not the issue with recommender systems, since any solution to improving online recommendations will likely require some form of AI.[1] A core problem with current approaches is that they derive recommendations primarily from human behaviour, often simply to keep us engaged on the platform. People's choices provide important information about what matters to them, but, as Amartya Sen forcefully argued, their choices cannot provide a full account of their motivations.[2] Perhaps the most salient reason for this gap is that choice does not necessarily reflect a maximization of preferences and can be driven by other motives.[3] For example, choosing to engage with misleading information online reflects a constraint in the quality of information available rather than a preference for false information.[4]

So, recommender systems based on behaviour do not provide an opportunity for people to ground recommendations on a broader set of aspects of what matters to them. This is key for human development, since it relates to the extent that people can exercise their agency and, ultimately, their freedom.[5] From a human development perspective this is a fundamental concern, perhaps less visible than other problems, with behaviour-based recommendations, which include both the exploitation of what psychologist Daniel Kahneman called system-1 thinking (behavioural biases that digital platforms exploit for engagement)[6] and the difficulty of accounting for heterogeneity in preferences.[7]

Recommender systems could be giving poor recommendations,[8] but more importantly they are shaping the choice architecture online and perhaps impoverishing the concept of what it means to be human, if what people do online is assumed to represent what people want to see.[9] Recommender systems are thus biased to make people more passive recipients of online content, rather than active agents able to access what matters to them, potentially undermining people as moral agents through moral deskilling.[10]

Moreover, recommender systems optimized for engagement, particularly in social media, seek to maximize the attention users devote to the platforms and to give content producers more opportunities to have their creations seen. Of course, this is driven also by the revenue-generation model of the platforms, which is determined primarily through engagement by both content consumers and producers, with higher engagement providing more opportunity to sell advertising that can be targeted.[11] There is an active debate on how to develop recommender systems optimized for things other than engagement, given some of the individual and collective harms associated with these systems.[12] But whether recommender systems could be optimized for something else relates also to the possibility of going beyond relying on online behaviour as the basis for recommendation, so that in addition to what people do online, recommendations could match who they are and what they value and have reason to value.

One possibility is to use some sort of "middleware" that mediates between the digital platform and the users.[13] But this would still not enable recommendations to reflect users' preferences and beliefs. Another possible approach would be to use large language models, given their ability to call on other tools (say, a search engine or a calculator) to execute tasks that go beyond their immediate training or that are required by the user prompt.[14] When recommender systems were first developed, algorithms could not engage in regular spoken language and could not explicitly reason the same way current models can.[15] The flexibility and adaptability of large language models provide options to explore how they can be used as agents,[16] if progress is made in addressing some of the inherent limitations of the technology,[17] including privacy, security and trust concerns.[18] A generative AI recommender agent could learn about what matters to the user by engaging conversationally—for example, by asking about what he or she values and has reason to value[19]—and iteratively compile content that aligns with those values and preferences.[20] Rather than taking human agency away from the interaction with digital platforms, these recommender agents could scaffold human agency in the interaction with online content.[21]

Notes

1. Li and others (2024) provide a survey of recent developments. See also Shen and others (2024). **2.** Sen 1973, 1977. **3.** Sen 1997. For a summary of Sen's view on preferences and choice see, for instance, Anderson (2001). For a recent critique that extends to the broader challenge of framing AI alignment as being driven by the rational maximization of preferences, see Zhi-Xuan and others (2024). **4.** Stewart and others 2024. **5.** Sen 1985. **6.** Agarwal and others 2024; Besbes, Kanoria and Kumar 2024; Kleinberg, Mullainathan and Raghavan 2024; Kleinberg and others 2024. **7.** Chen and others 2024; Yao and others 2024. **8.** Rita Gonçalves and others 2025. **9.** Agan and others 2023. As noted above, there are also privacy concerns, with technical options being pursued to address these but without fundamentally changing the behaviour-based engine of the recommendation (Chronis and others 2024). **10.** Schuster and Lazar 2025. **11.** A different challenge relates to moderation, which deals with the choices that platforms make on what content to allow in order to comply with the law and each platform's terms of service, as well as how to achieve those goals (outsourcing fact checking, using algorithms to detect prohibited content or having users flag noncompliant content). On moderation in digital platforms, see Douek (2022), Gorwa, Binns and Katzenbach (2020) and Lai and others (2022). On tensions between free speech and moderation and ways of addressing them, see Kozyreva and others (2023). Moderation and recommender systems optimized for engagement might not be independent, because content that elicits more engagement is often extreme and close to the bounds of what is accepted, so there might be an inherent tradeoff between effective moderation and current recommender systems (Narayanan and Kapoor 2024). **12.** Bernstein and others 2023; Cunningham and others 2024; Ho and Nguyen 2024; Jia and others 2024a; Kazienko and Cambria 2024; Singh and Joachims 2018; Stray 2020; Stray and others 2024; Wang and others 2023. **13.** Hogg and others 2024. **14.** Askari and others 2024; Pentland and Tsai 2024. **15.** Lazar and others 2024. **16.** Kapoor and others 2024b; Wang and others 2025; Xi and others 2023. **17.** For applications in medicine and healthcare as an example, see Kim and others (2024), Kim and others (2025) and Wang and others (2025). For applications that include but go beyond medicine, see Wölflein and others (2025). **18.** Andreoni and others 2024. **19.** Danry and others 2023. **20.** As proposed by Schuster and Lazar (2025). **21.** Lazar 2024b; Schuster and Lazar 2025; Whitt 2024. Some emerging examples of related approaches include Irvine and others (2023), Jia and others (2024b), Paul and others (2024), Yuan and others (2024) and Zhao and others (2024).

certain actions, otherwise presuming a baseline of freedom. In contrast, recommender systems start from the opposite end, where people's choices are shaped by what the recommender system suggests or determines is feasible. By governing the rules and policies of data curation and moderation, digital media platforms today shape "power over." Platforms decide how to up-rank or down-rank posts, flag and remove content, suggest new contacts or altogether ban a user, curbing their overall social engagement in that space.[52] These decisions have far-reaching consequences for social choices and prospects.[53]

Recommender systems not only arbitrate power over individuals—they also redefine power relations between them.[54] They can allow behaviours that are malicious or abusive, excluding or harming segments of the population.[55] By shaping power relations between the people they mediate, algorithmic intermediaries enable some users to exert influence over others, affecting their prospects and choices. Moreover, as a result of numerous, repetitive social interactions, recommender systems are reconfiguring societal structures, including social norms, institutions and culture—reshaping political discourse and deliberation.[56]

Automated power and its implications

As algorithms upend power relations, they operate like multipliers, enabling fewer people to have bigger impacts on others' lives.[57] Elsewhere, computational systems act as automatic arbiters of power, leaving decisionmaking to machines, raising questions about legitimacy.[58] Consider how algorithmic tools are being used in various parts of government services, ranging from allocation of social security benefits to criminal justice and security issues.[59] Or how algorithms in social media act dynamically, monitoring the social relations they mediate in real time, as we just saw. Their capacity to actively shape social relations and curate the information accessed grants them far-reaching influence, positioning them not merely as passive facilitators but as active agents in both the digital and real worlds.[60]

AI is being layered on a changed digital information environment that was already presenting new challenges to collective decisionmaking even before the advent of generative AI (spotlight 5.1).[61] Generative AI may exacerbate challenges ranging from making political microtargeting more persuasive and scalable[62] to the potential for political bias in outputs produced by generative AI models.[63] And yet, it is crucial to avoid the technodeterminism examined in chapter 4 and attributing to technology causal harms that may often have more to do with underlying psychological, social, and political challenges.[64]

> "Generative AI may exacerbate challenges ranging from making political microtargeting more persuasive and scalable to the potential for political bias in outputs produced by generative AI models. And yet, it is crucial to avoid technodeterminism and attributing to technology causal harms that may often have more to do with underlying psychological, social, and political challenges

Still, consider how AI is making "hypersuasion" possible—that is, influencing beliefs and behaviours by crafting language aligned to its users' psychological profiles. Large language models can generate responses based on users' specific profiles—such as their personalities, moral values or political ideologies.[65] Information about users' profiles can be mined from online behaviour—such as online readership, social media activities, shopping patterns and feedback on large language models. Hypersuasion in turn can generate behaviour or shape attitudes, raising ethical concerns and the possibility of harm through malicious intent.[66] Further, taking users' behaviour as expressive of true interests and opinions interferes with the formation of democratic, private and public judgements, potentially undermining people's agency (see box 5.1). In some cases AI is as good as or better than humans in hypersuasion. The latest large language models passed theory of mind tests that are practiced on humans, even though, in line with the main argument of this Report, anthropomorphizing framings and language need to be considered with caution.[67] AI does not suffer from egocentrism biases the way humans do,[68] and given that AI has access to much wider sets of language than any human could possibly have, the responses from AI can be particularly persuasive.[69]

Beyond hypersuasion being automated at scale, several large language models have exhibited sycophancy—the tendency to generate responses attuned to user tastes over accurate and impartial responses.[70] This is observed in large language models trained to provide neutral or diplomatic answers but also to be responsive to user feedback, so over time their responses evolve to be more in line with user opinions, potentially hampering accuracy and reliability.[71]

Power is also being exercised through algorithmic governmentality—the use of algorithms to assess, predict and control the behaviour of populations. The concept stems from Michel Foucault's governmentality, or how power is exercised through knowledge (about the subjects being governed) to navigate towards certain outcomes through specific instruments. Data can be gathered to build detailed profiles of people, categorize them into groups, predict their future behaviour, direct them towards certain action or treat subjects differently. Examples include microtargeting populations for votes, predictive policing and determining social security benefits for individuals. The exertion of power in these new ways is simultaneously complemented by the disempowerment of people whose data are being shared, often without their knowledge, leaving them unaware of how it could be used to determine outcomes in their lives.[72]

Can AI be used to enhance collective action?

While AI risks influencing political processes, it alone may not be the most important determinant of potential impacts. For example, generative AI has reduced the cost of producing false, manipulative content, but the cost of distribution remains the binding constraint in having societywide implications.[73] In 2024 Wired magazine gathered data from more than 60 countries to understand AI use in manipulating information prior to elections. Of 78 deepfake cases, half were not intended to deceive; further unpacking the demand side of false or misleading information flows is required rather than looking at the supply side alone.[74] Concerns that much better large language models would supercharge the persuasiveness and scale of political messages appear not to be panning out, since newer and larger models do not substantially increase the persuasiveness of political messages compared with earlier large language model releases.[75]

Moreover, several initiatives seek to address the potential harms of AI for collective decisionmaking and action. The United Nations Educational, Scientific and Cultural Organization's Recommendation on the Ethics of Artificial Intelligence, adopted in November 2021, provides a global policy framework for guiding AI use to uphold human rights and dignity and ensuring that AI benefits societies at large.[76] Updated in 2024, the OECD AI Principles are another set of intergovernmental standards on AI, with 47 adherent countries, providing a basis for developing AI that respects human rights and democratic values.[77] Launched in 2019, Singapore's Model AI Governance Framework is paving the way for a strong AI ecosystem that balances innovation with concerns around security, privacy and accountability, among others.[78] Its objective is to make AI human-centric by providing practical guidelines to the private sector to ensure governance and ethics in product development.[79]

> “The Global Digital Compact, agreed by the United Nations General Assembly in late 2024, is unique and exceedingly important, as elaborated further below, for helping different jurisdictions shape the supply of AI according to the universal principles of the United Nations Charter and the Universal Declaration of Human Rights

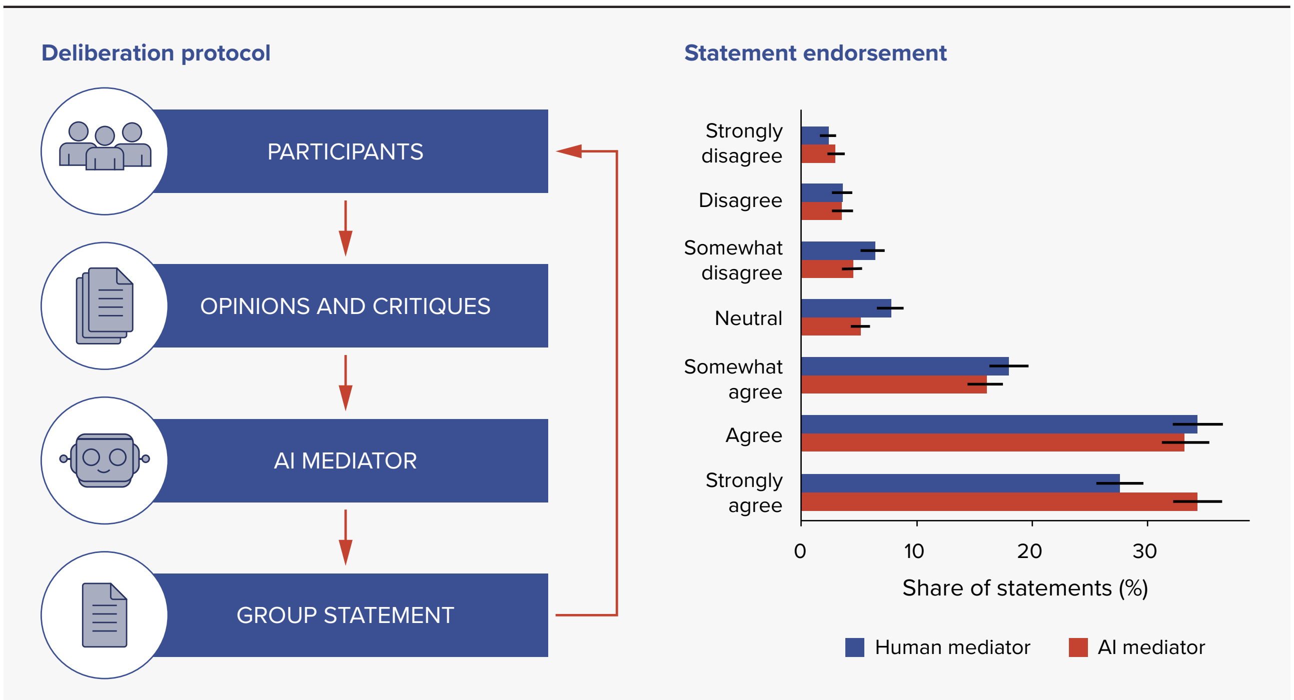
These frameworks aim to ensure that AI is produced in a way that abides by ethical principles that support collective action and increase social welfare. But they are not universal. In that context the Global Digital Compact,[80] agreed by the United Nations General Assembly in late 2024, is unique and exceedingly important, as elaborated further below, for helping different jurisdictions shape the supply of AI according to the universal principles of the United Nations Charter and the Universal Declaration of Human Rights.

Many initiatives are exploring the use of AI to enhance collective action.[81] For example, deliberative collective action rests on the understanding that individuals are autonomous beings with their own set of values and beliefs and have capabilities—and more critically equal rights—to determine the laws and policies that govern them.[82] One key constraint in these processes that AI could help tackle is the practical challenge of mass participation. Citizen assemblies, for example, are difficult to scale and often result in voices being heard unequally. AI-powered tools could synthesize inputs from numerous people to present a picture of how the population sees issues that affect them. An example is Polis,[83] a machine learning tool that gathers opinions, categorizes them into themes and tries to understand what large groups of people think.[84] One of its innovative features is that it does not have a reply button, which mitigates negative back and forth conversations and redirects focus to the expression of novel ideas.[85] AI tools are also providing deliberators with useful resources, such as reliable data and information, to guide collective decisionmaking.

AI can further enhance the quality of human-to-human interactions by facilitating peaceful, productive dialogues. For example, AI-based interventions in online chats can improve political conversations and do so at scale.[86] When people are discussing issues that divide them, AI can support mediation by generating and refining statements that express common ground.[87] An experiment of a virtual citizens' assembly in the United Kingdom showed that a trained large language model could outperform humans in bringing people together on contentious issues such as Brexit, migration, the minimum wage and climate change (figure 5.4).[88] Group statements compiled using large language models were more acceptable to the group than those generated by human mediators. Another experiment demonstrated that AI could successfully counter beliefs in conspiracy theories by providing alternative facts and engaging in evidence-based dialogues.[89] These examples highlight how AI could mitigate divides, advancing collective action.

AI can also help build a healthier ecosystem for online conversations. Perspective API, launched in 2017 by Jigsaw and Google, facilitates online conversations by flagging malicious content and removing or down-ranking it.[90] More recently, the tool was augmented to prioritize content that moves groups towards constructive dialogue by identifying reasoning, storytelling and curiosity in conversations.[91] Readers on average found that the conversations were not only less hostile but also more interesting, trusting and respect-worthy.[92] Publicly available large language models, when fine-tuned to give equanimous perspectives on issues of debate, can expose users to a spectrum of opinions and could nourish public discourse.

Figure 5.4 Artificial intelligence (AI) outperforms human mediators in finding common ground



Source: Tessler and others 2024.

Who has the power? Divides and dependencies are evolving amid furious AI races

From the printing press to the spinning jenny to nuclear fission, technological trajectories have long been shaped by people's choices.[93] Algorithms take this to a new level: they are literally codified choices about everything from user feeds to online marketplaces.[94] Economist Martin Shubik, commenting on Herbert Simon's famous lecture on designing organizations for an information-rich world, described human societies as information processing systems.[95] Human lives are built on decisions made on the basis of that information processing. AI-powered algorithms reflect a fundamental change in how information is processed in our societies, how individual and collective decisions are made and how people live their lives.[96] Algorithmic choices do not just dominate the digital sphere, they constitute it.

"AI-powered algorithms reflect a fundamental change in how information is processed in our societies, how individual and collective decisions are made and how people live their lives. Algorithmic choices do not just dominate the digital sphere, they constitute it

The scope, speed and reach of algorithmic choices are mindboggling, and they matter for human development. Our societies—their laws, norms, institutions and leaders—codetermine the choices available to us and the ones achievable. That is why understanding the ways algorithms mediate our social interactions and social choices matter so much. That is also why it is important to understand the supply side of who is making decisions about how those algorithms work.

Most of us have little direct say over algorithms. What choices trickle down to us are a hard residue, atomizing and binary: buy the latest gadget or not, accept the cookies or not. Take-it-or-leave-it terms of service agreements can boil down to, on the one hand, granting Big Tech carte blanche access to our daily lives in their quest to build bigger and more profitable garrisoned database or, on the other, exclusion from colossal digital platforms, where for better and worse ever more of our lives, interactions and relationships take place. A digital exile exempt from due process.

The freedom to have and exercise more choices over technologies that can powerfully influence people's opportunities is itself a concern of—and for—human development.

The opportunity for more choices by and for people seems huge, if bounded in some degree by technological feasibility and by the decisions of those supplying AI. As noted above, digital technologies pose unique challenges to traditional policy interventions to address market concentrations and expand consumer choices.[97] For example, digital platforms can be understood as essentially selling access to people's attention to advertisers, but when there are only a few players, the concentration of this bottleneck in attention is detrimental to advertising firms and consumer welfare, something that traditionally is not considered by competition authorities.[98] This new challenge is perhaps one reason different jurisdictions have taken varying views on whether and how to regulate digital markets and platforms for many years and on AI more recently.[99] Regulation choices are also shaped not only by the affordances of the new technologies but also by differences in institutions and varying interpretations of the state's role in the economy.[100]

For example, the United States has emphasized innovation and light regulation of AI, while the European Union has prioritized individual protections and potential social harms, establishing comprehensive regulations through laws such as the Digital Markets Act, the Digital Services Act and the General Data Protection Regulation.[101] China follows a state-driven model.[102]

While identifying the precise boundary of technologically feasible choices may be hard, an ongoing tension on regulation is clearly driven by the motives of incumbent companies, often concentrated, as seen above—and by the concerns of people, workers and governments about the negative impacts of the power concentration documented in this chapter, which some years ago resulted in what was described as a "techlash."[103]

The concentration of power in those making choices on what kind of AI to supply has consequences for people. Algorithms that maximize user engagement are a choice, a lucrative one that may amplify outrage. Moderating content (or not) is a choice. So is the degree of openness. Many leading AI firms have been reluctant to fully open their AI models, including the underlying training data.[104] Companies select benchmarks against which their latest models are evaluated. One well-known benchmark is apocalyptically dubbed Humanity's Last Exam and pits machines against people.[105] If we want humans and machines to compete less and complement each other more, we should stop letting bullseyes be placed on our backs.

Another manifestation of the restriction of choice is the AI race, an epic spending spree by Big Tech, whose market capitalizations have ballooned since ChatGPT burst onto the scene.[106] The race is rapidly evolving, and how it shakes out is anybody's guess, but a combination of hype and a bigger-is-better paradigm appears to be fuelling it.[107]

A simplified AI supply chain hinges on three key inputs—computing power (which goes by "compute" in the AI industry jargon) talent and data—in and through which divisions and dependencies among companies and countries are evolving. Low-income and many middle-income countries face yawning gaps in each input. Steps can be taken to address gaps, but these countries need to be strategic. The vast majority simply do not have the luxury of spending billions in a high-stakes AI race.

> "We should also take a step back and question whether narratives anchored in zero-sum competition miss opportunities for cooperation and gains for all players, including across countries. Finding opportunities to steer a mix of cooperation and competition towards human development, towards expanded choices and opportunities for people, is the task at hand

The relationship between countries is not just competitive or confrontational. Governments can be partners, regulators and competitors, sometimes simultaneously and in different ways. India plans to set up a common compute facility to support AI development,[108] including among researchers and startups. The United States announced the Stargate Initiative,[109] a $500 billion partnership between such recognizable tech titans as Nvidia, OpenAI and Oracle and Japanese financial conglomerate Softbank. The initiative aims to build AI infrastructure in the United States. The European Union has responded with its own €200 billion partnership with InvestAI.[110]

In these heady early days of generative AI, countries are staking out positions in light of how they see it impacting their different interests—from geopolitics to security to growth and development. Given the variety of interests in play and the evolving, complex relationships among players, especially between countries and firms, we should stop talking about an AI race and instead talk about many AI races. We should also take a step back and question whether narratives anchored in zero-sum competition miss opportunities for cooperation and gains for all players, including across countries. Finding opportunities to steer a mix of cooperation and competition towards human development, towards expanded choices and opportunities for people, is the task at hand.

AI models depend on three unevenly distributed inputs: Compute, talent and data

Compute

About 60–95 percent of recent performance gains in AI have stemmed from scaling compute,[111] though it is unclear whether scaling will remain the driving force for improved AI performance.[112] The training compute of notable machine learning models has been increasing by a factor of 4.7 each year since 2010.[113] Part of the expense of compute is due to remarkable concentration in the semiconductor market, particularly for advanced AI chips, where Nvidia holds a dominant position.[114] The concentration is even more pronounced in the equipment to make chips, which is effectively controlled by a single company, ASML.[115] The massive fixed costs involved, combined with low variable costs, favour economies of scale,[116] contributing to a highly concentrated chip market.[117] As major cloud providers develop their own chips, this vertical integration risks concentrating power in new ways.[118]

Apart from the cost of chips themselves, AI data centres have voracious appetites for energy and water.[119] Google is turning to small nuclear reactors to power AI data centres, and other big corporations are reconsidering their climate commitments given AI's energy demands.[120]

Talent

People are the main drivers of innovation and the custodians of knowledge. The critical role of people driving and disseminating innovation is one reason open-source approaches have gained ground in the AI industry.[121]

The demand for talent is increasing, outstripping supply that can take time to fill given the bevy of specialized skills required. Even as early as 2021, many organizations struggled to fill AI-related roles.[122]

Meanwhile, industry is siphoning talent from academia. The proportion of AI Ph.D. graduates entering industry rose from 21 percent in 2004 to 73 percent in 2022.[123] Industry provides not only higher financial incentives but also access to substantial computing resources. It often also provides researchers with opportunities to deploy cutting-edge technologies. Governments face similar disadvantages in AI talent.

Data

The data requirements of AI models can be vast, which affords advantages to some companies and countries over others. Digital platforms and social media firms have accumulated massive amounts of proprietary data over the years, due largely to positive network effects, which amplify the value of a product or service as more people use it.[124] While network effects are less clear with AI, data feedback loops, in which AI gets better and more attractive to users as their interactions with it deliver more data, can also play a role.[125]

Large proprietary databases are set to take on greater importance as the current crop of large language models exhaust the supply of publicly available data and as public datasets increasingly contain AI-generated output, though this depends on the evolution of algorithms. For example, reinforcement learning training methods may put a premium on domain-specific and high-quality data or even synthetic data that are model generated (while not a perfect analogy, think of the way AlphaGoZero and AlphaZero were trained to play, respectively, Go and chess). A recent analysis of the private data available on major closed content platforms, instant messaging applications and email services suggests that leveraging nonpublic data could delay a potential data bottleneck by approximately 18 months compared with relying solely on indexed web data.[126] Moving from pretraining to posttraining of AI models, proprietary data have obvious significance for fine-tuning models for specific applications such as drug discovery.

One example is Shoshana Zuboff's point of view, which sees corporations extract and commodify all kinds of behavioural data, transforming user activity into a competitive resource characterized by a lack of user awareness and transparency.[127] It is also easy to see how this could extend to governments' surveillance capacities, by either using their own databases on people or gaining access to databases maintained by companies. A recent study argued that the emergence and persistence of market power around AI would be shaped largely by how data markets operate—in particular, whether trading data across firms' boundaries would take place.[128]

Low-income and several middle-income countries face big gaps in key AI inputs

Countries are increasingly being evaluated for their ability to develop and deploy AI based on how prepared, ready and vibrant their AI ecosystems are. Multiple global indices and tools now compare national AI capabilities, though their scope and methodology differ widely. Insights from these indices highlight gaps across low- and several middle-income countries along various dimensions (table 5.2).

Several factors determine a country's ability to develop AI. Examining a country's science–technology nexus[129]—the interconnected and reciprocal relationship between scientific research and technological progress—is one way to assess this ability. The nexus depends on a country's pre-existing technological capabilities, the strength of its scientific knowledge base and the alignment between the scientific and technological sectors.[130]

High-income countries such as the United States, the Republic of Korea, Japan and Germany, in that order, have well-established digital infrastructures, giving them a major advantage in AI development. In contrast, low-income countries may lack the

Table 5.2 Gaps across country income groups based on popular artificial intelligence (AI) metrics

Global AI Vibrancy Tool	Government AI Readiness Index	AI Preparedness Index	Global AI Index
Highlights gaps in AI activity, development and impact across countries. Among 36 evaluated countries, only India (ranked 4th) is lower middle income—showing low AI vibrancy in lower-income countries.	High-income countries traditionally lead due to mature tech sectors. 2024 data show low- and middle-income countries improving in governance, ethics and data strategies—potentially closing gaps.	Wealthier economies (advanced and some emerging markets) are better prepared for AI adoption. Considerable variation exists, with low-income countries lagging.	China and the United States dominate across investment, innovation and implementation. The next eight countries are closer in rank, with India as the only low- or middle-income country in the top 10. The remaining 73 countries trail behind.

Source: AIPI 2025; Oxford Insights 2023; The Stanford Institute for Human-Centered AI 2025; Tortoise Media 2025.

digital infrastructure to even deploy, let alone supply, AI tools. The United States, China, the United Kingdom, Germany and Canada also lead in scientific knowledge production, with the United States and China holding a distinct advantage.[131]

One of the three pillars of the Government AI Readiness Index is the Technology Sector,[132] which assesses the maturity of a country's technological infrastructure. This pillar also reflects the disparities in ability to develop AI across countries, similar to those in the science–technology nexus. When focusing solely on the Technology Sector pillar, high-income countries generally outperform others, with the United States standing out due to its mature market and high innovation capacity. Other high-income regions, such as Western Europe, also perform well but typically lag behind the United States in this area. In contrast, low- and middle-income countries in Sub-Saharan Africa and Latin America and the Caribbean exhibit substantial gaps.

Most large-scale AI models today are developed by organizations based in the United States, followed by China and the United Kingdom.[133] Only a small fraction originates from other countries, including Saudi Arabia and the United Arab Emirates, and very few are created through international collaborations (figure 5.5). Investment is also concentrated in the United States and China (figure 5.6).

Gaps in AI capabilities

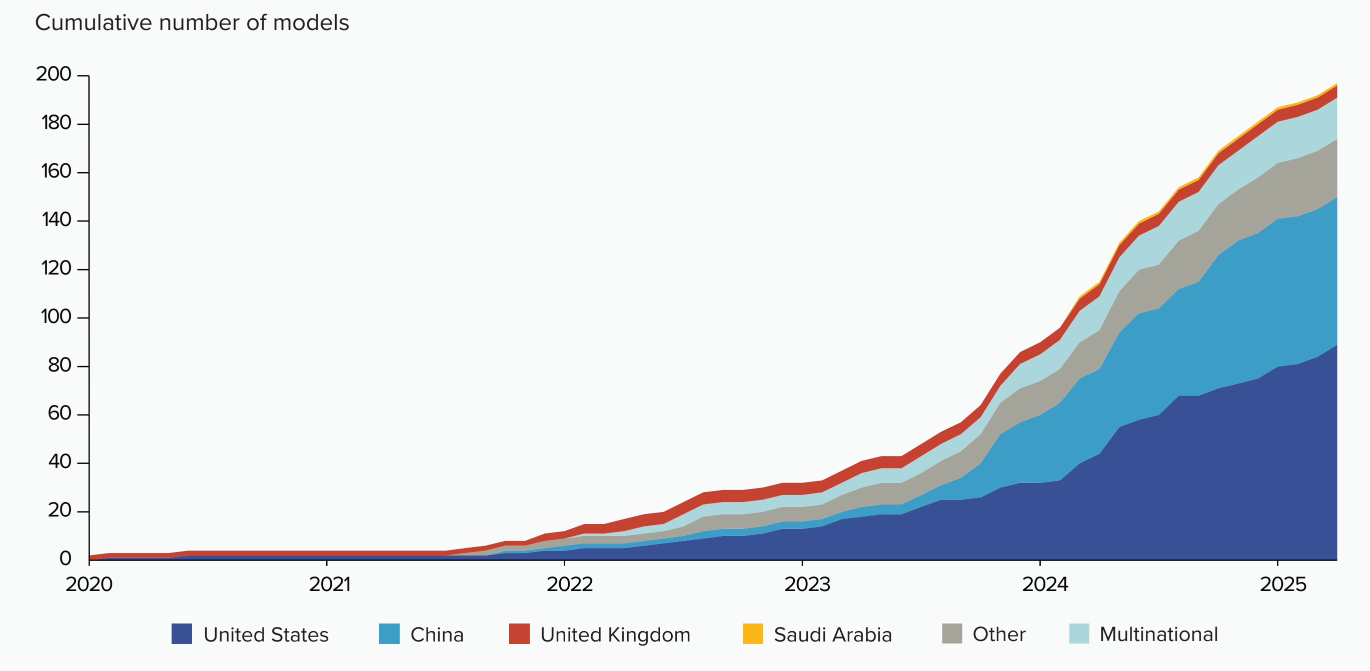
As of March 2024, the United States hosted about half the global data centres,[134] reflecting the concentration of that infrastructure.[135] Although cloud computing relaxes the link between the physical locations of data centres and data use, only 5 percent of Africa's AI talent has access to the computational power for complex AI tasks.[136] Big Tech dominates global AI computing power, owning much more than many national governments.[137]

The availability of data for AI development in a country depends on several factors, which can be assessed through the Data Availability dimension of the AI Readiness Index's Data & Infrastructure pillar.[138] Data availability varies considerably across countries and regions. Middle-income countries are improving their data ecosystems through stronger policies and governance. However, many struggle with data representativeness due to gaps in internet access. Sub-Saharan Africa is making progress in data availability and infrastructure but still shows large gaps. These disparities stem from differences in government commitment to open data, data management capabilities and access to technology.

There is a stark divide in AI talent between low- and middle-income countries on the one hand and high-income economies on the other.[139] The United States attracts 60 percent of elite AI researchers (roughly the top 2 percent) and hosts 75 percent of top-tier talent educated in US or Chinese institutions. While China now retains 47 percent of its homegrown researchers—up from 29 percent in 2019—most lower income countries struggle to retain talent. India has also made progress in retaining talent: 20 percent of its AI researchers now stay domestically (up from near zero in 2019).[140]

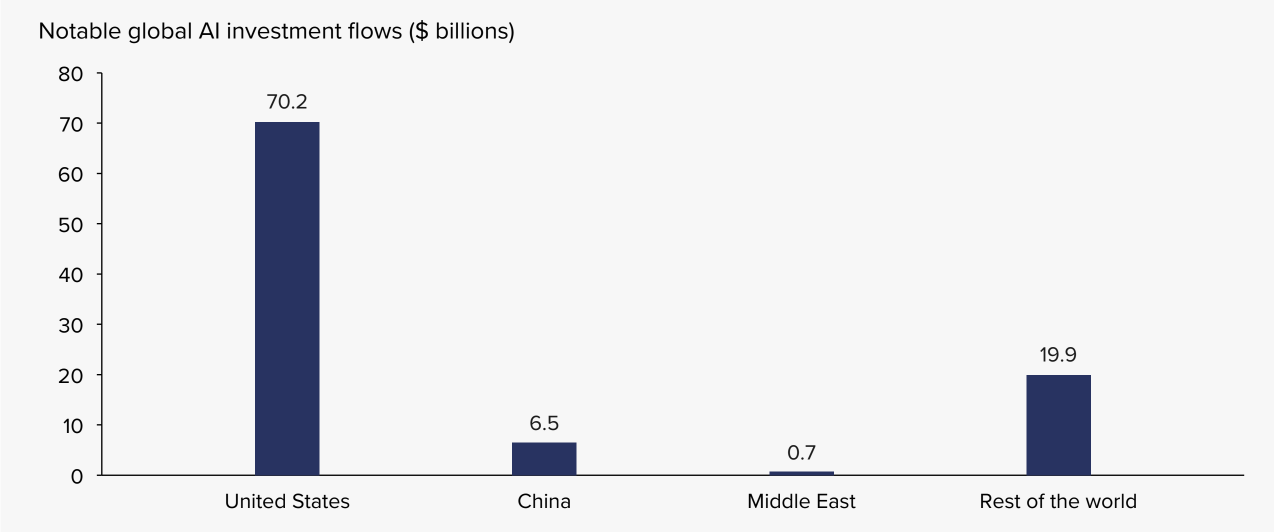
High-income countries such as the Republic of Korea, the United Kingdom and the United States leverage existing infrastructure and funding to attract talent, while emerging economies face an uphill battle. This entrenches a cycle where innovation clusters in wealthy countries, risking leaving others further behind in AI innovation, supply and deployment.

Figure 5.5 The majority of today's large-scale artificial intelligence models are developed by organizations based in the United States, followed by China and the United Kingdom



Source: Epoch AI 2024d.

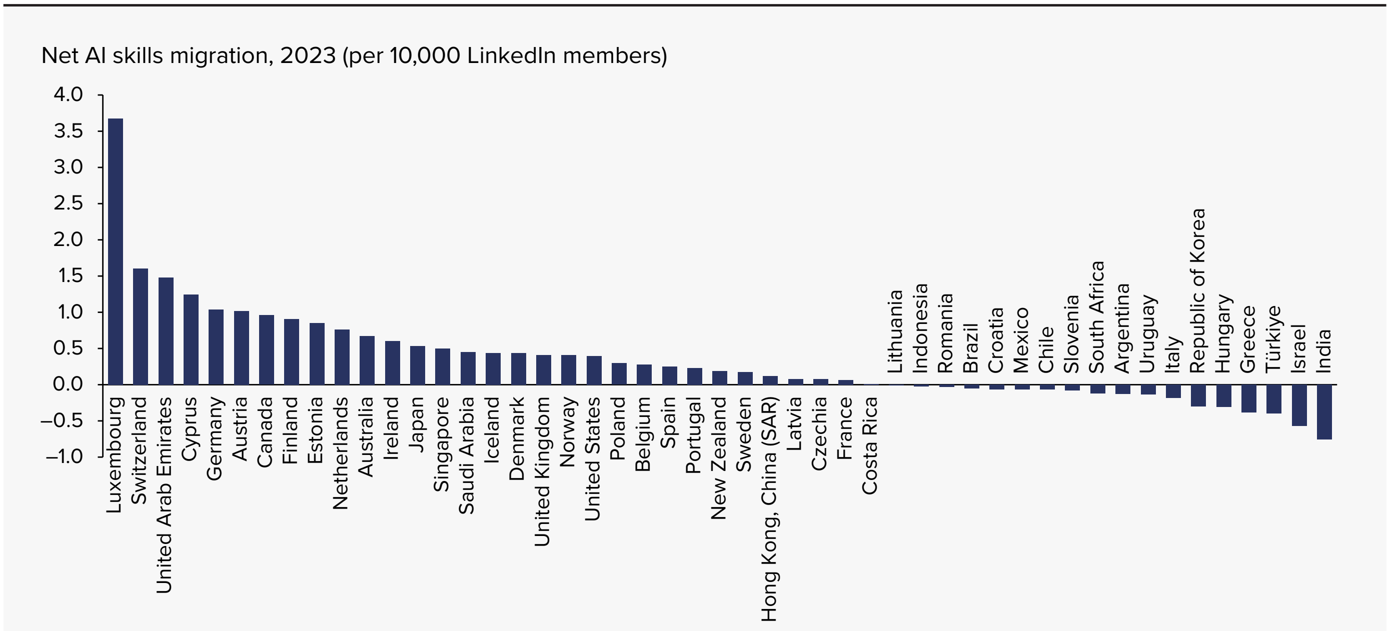
Figure 5.6 Most global investment in artificial intelligence (AI) flowed to the United States in 2024



Source: Lucidity Insights 2024.

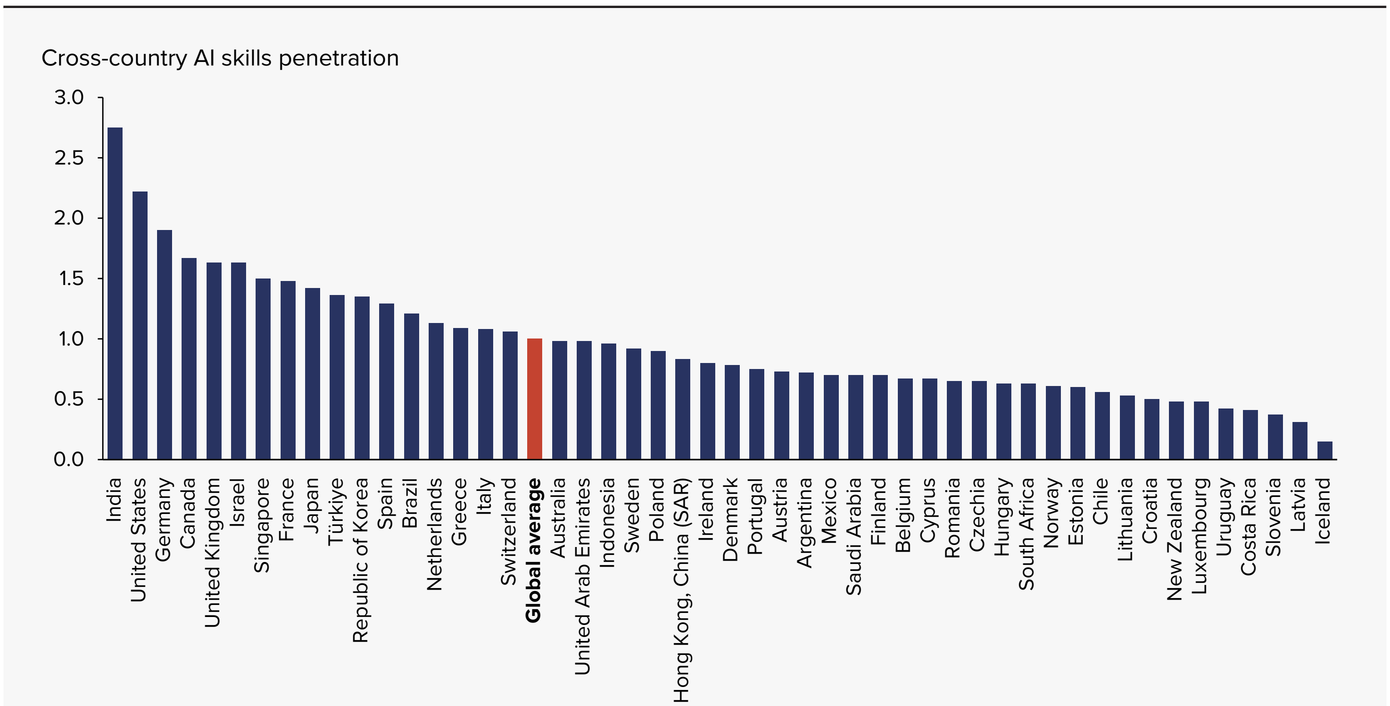
These disparities are also revealed by a widening chasm in AI talent distribution between 2019 and 2023.[141] In 2023 high-income countries saw a net gain in AI talent, while low- and middle-income countries experienced a net loss (figure 5.7). India has the highest self-reported AI skill prevalence globally (figure 5.8), but even as lower income countries cultivate talent pools, systematic gaps in compute, data and institutional support drive net losses, as skilled workers migrate to higher income countries.

Figure 5.7 Artificial intelligence (AI) talent has been flowing towards high-income countries



Note: The figure shows net migration flows (of LinkedIn members with AI skills) in 2023. The bars indicate the magnitude of a country's net AI talent gains (or losses), normalized by the total LinkedIn membership in that country (and multiplied by 10,000).
Source: OECD 2025a.

Figure 5.8 India has the highest self-reported artificial intelligence (AI) skills penetration



Note: The figure shows the prevalence of workers with AI skills (as self-reported by LinkedIn members) by country and against a global average benchmark (as shown by the red bar). A relative penetration rate of 2 means that the average penetration of AI skills in the country is twice the global average across the same set of occupations.
Source: OECD 2025a.

A geopolitical innovation race is taking shape

The AI races[142] can be interpreted as unfolding along a spectrum, from a collaborative innovation race to a purely zero-sum arms race (figure 5.9).[143] This spectrum reflects different ways of considering ongoing AI competitive dynamics.[144] The nature of the race is not inherent to AI itself but emerges from how agents interpret and respond to the actions and perceived interests of others.

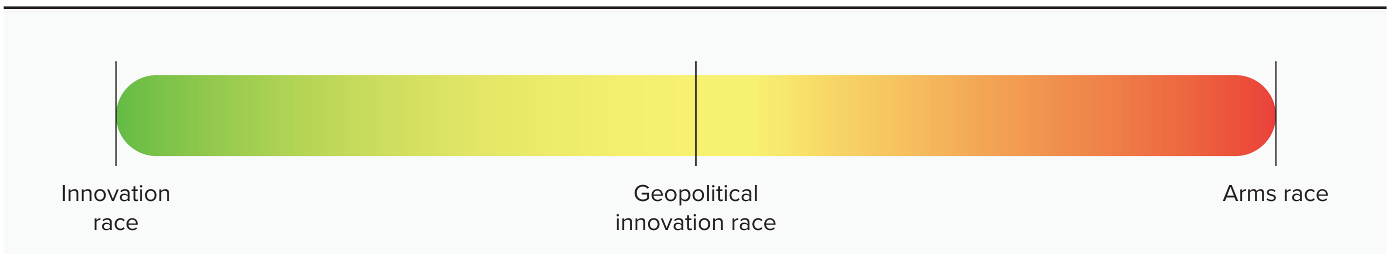
The perception of a race itself can become self-fulfilling, where agents, believing they are in zero-sum competition, prioritize speed and achieving breakthroughs over safety and ethical considerations.[145] Motivations are not solely about security; they are also heavily influenced by economic and status concerns,[146] with countries vying for technological, economic and political leadership. This mix of motivations is entangled with security concerns, as countries aim to defend their territory and enhance their international competitiveness and reputation. The interactions are characterized by a mix of competition and collaboration, in complex and shifting networks.[147]

Big Tech is also part of the agents involved, given that it operates transnationally, extending its reach and influence.

Their operations involve moving data and services across international borders, making them important players in various regions. The transnational operations of Big Tech are fraught with tensions and challenges due to the diverse regulatory landscapes, as companies must comply with varying requirements in different regions. This is apparent in the way app stores control software on devices and in the way data labelling in some countries affects labour conditions in others.[148] For instance, the EU General Data Protection Regulation sets stringent data protection standards that non-European companies must adhere to if they wish to operate in Europe,[149] demonstrating the European Union's ability to influence global data practices. This is an example of the "Brussels Effect,"[150] wherein EU regulations can become de facto international standards, as companies adopt them to reduce costs across jurisdictions.[151]

These differences put in sharp relief the importance of the UN Global Digital Compact.

Figure 5.9 The artificial intelligence (AI) race today can be conceptualized as unfolding along a spectrum spanning innovation to arms



Innovation race	Geopolitical innovation race	Arms race
The innovation race involves multiple actors—including companies, states and research institutions—competing for technological leadership with more collaborative networks and looser relationships between actors. This race is motivated by a mix of economic and status gains, viewing AI as a key technology for broad socioeconomic advancement. This race is generally collaborative and competitive, with actors striving for innovation and the expected payoffs of a technological breakthrough shaping incentives.	The geopolitical innovation race is a hybrid concept that combines elements of the innovation race and the arms race. It involves competition for technological leadership but also features a mix of competition and collaboration within national borders, or technopoles. This race is characterized by economic and status concerns intertwined with security and power interests, with AI viewed as a key technology for national security and power with limited interpretative openness. It is a race in which state actors play a crucial role in funding and regulating technological development. It can have both positive and negative outcomes.	The arms race is characterized by intense, zero-sum competition, primarily among states, focused on military capabilities, with tightly coupled national networks. This race is driven by security concerns, where states seek to gain relative advantages and often treat technologies such as AI as a weapon or part of a weapon system. In this race there is continuous competition and investment, with actors envisioning (relative) advantages and seeing no scenario of possible collaboration. This race is criticized for potentially inducing researchers to prioritize speed over safety and ethics.

Source: Schmid and others 2025.

Implementing provisions such as a continuous dialogue across jurisdictions on how to approach AI regulation—a dialogue informed by science and in which countries not at the forefront of AI supply have a chance to engage will be crucial. Uncertainties around the future of AI as a technology and sharp differences across jurisdictions may not make a universal set of regulations feasible, but everyone, firms included, stands to benefit from implementing these and other provisions of the Global Digital Compact (box 5.2).

What are the possibilities for international action on AI?

Whether one race among AI developers or many AI races among an evolving complex of countries and tech companies, a zero-sum mindset seems to pervade AI efforts. It is leaving many countries and people behind. It misses opportunities for international cooperation that could promote and more equitably distribute shared benefits on the one hand and better manage shared risks on the other. Competition and cooperation can not only coexist; they can also work together to spur innovation and deliver better outcomes for everyone.

Low- and many middle-income countries will need support to get started on their own AI supply journey. Opportunities for cooperation exist, as in pooling access to AI-related infrastructure, sharing expertise and, where possible, developing common policy positions—that can ease entry and distribution of desired technologies while bolstering negotiating positions. AI also presents opportunities for Indigenous peoples by offering tools for language preservation, but there are concerns about data ownership, misrepresentation and the need for Indigenous participation in AI development to ensure cultural integrity and sovereignty (box 5.3).

National policies on AI, nascent and evolving, will need to be flexible as the technology and its applications continue apace. Different countries have so far staked out positions that overlap in some ways and differ in others. Coverage of important regulatory domains is uneven within and across leading AI countries.[152] Varying national approaches can act as laboratories for experimentation and innovation. Striking the right balance is key, as regulatory

Box 5.2 The UN Global Digital Compact for addressing power imbalances and fostering inclusive artificial intelligence

> "A world of AI haves and have-nots would be a world of perpetual instability. We must never allow AI to stand for 'advancing inequality.' Only by preventing the emergence of fragmented AI spheres can we build a world where technology serves all humanity."
>
> *—UN Secretary-General António Guterres*

Signed by 193 countries at the Future Summit in September 2024, the UN Global Digital Compact brings together countries to strategize ways to make artificial intelligence (AI) safe, open and inclusive. It is anchored in the 2030 Agenda for Sustainable Development, with the goal of ensuring that the benefits of AI are equitably distributed and do not leave behind developing countries, especially the least developed countries. It is further guided by the principles of international human rights to ensure that all human rights—including civil, political, economic, social and cultural rights—are respected and safeguarded online and offline.

The compact articulates several key objectives that can help address power imbalances and ensure equitable access and opportunities. This includes closing the digital divide for all and helping advance the Sustainable Development Goals from education and health to inequality and governance. Those tasks are central in this effort to ensuring that no one is left behind, including youth and women innovators, as well as small and medium enterprise owners, who can meaningfully contribute to AI development.

International AI governance, a joint responsibility of all countries, is a key part of the compact. The aim is to govern AI in the public interest while ensuring that its applications promote diverse cultures and languages rather than increase biases. The compact recognizes the critical contribution of governments, civil society, the private sector and other key partners in its successful implementation.

Source: UN Global Digital Compact.

Box 5.3 More subtle manifestations of power emerge in artificial intelligence models' behaviour

Generative artificial intelligence (AI) systems are trained using around 90 percent English materials.[1] While one cannot directly tie training data to AI outputs, there is evidence that the predominance of English in training data matters.[2] In some large language models this is explicitly true, as non-English prompts are translated into and from English. In multilingual models (in which English is not explicitly used as a "pivot" language), AI appears to conceptualize words in ways that do not represent a specific language but align more closely with their English definitions.[3]

One study found that when multilingual models are prompted to make emotional statements, they respond with the expected emotion of someone from the United States.[4] AI models also reflect other biases,[5] though not always in the same way.[6] Some evidence shows that biases demonstrated in English texts are reproduced in other languages.[7] Still, other studies are less definitive, showing that ChatGPT is more effective at accurately assessing a culture's value in its native language than in English.[8]

Large language models trained almost exclusively on English materials can pose risks for cultural misrepresentation and even exploitation. Incorporating Indigenous languages into mainstream generative AI platforms, such as OpenAI's ChatGPT and Whisper, raises concerns over ownership of data produced by or about Indigenous peoples.[9] Technology companies often use data without the consent, consultation or compensation of Indigenous peoples,[10] mirroring other extractivist practices.[11] In accordance with the 2020 Los Pinos Declaration, which states "Nothing for us without us,"[12] Indigenous peoples' participation in new technology development is essential for enhancing their agency.

Despite the risks, AI systems developed and codeveloped by Indigenous peoples can be valuable tools for preserving cultures and languages. With half the world's roughly 7,000 languages predicted to be seriously endangered or extinct by 2100,[13] AI can be a valuable tool for language documentation and education. Te Hiku Media, a New Zealand Indigenous nongovernmental organization dedicated to Māori language revitalization, has developed an app to allow users to upload audio in Māori,[14] which will train AI models used in chatbots and language learning apps.[15] Such AI tools enable Māori speakers to access information that previously required foreign language knowledge. Importantly, this case demonstrates that such tools can be developed with processes that respect Indigenous peoples' data.

Notes

1. Achiam and others 2023; Cao and others 2023; Touvron and others 2023. **2.** Piir 2023. **3.** Caliskan, Bryson and Narayanan 2017; Wendler and others 2024. **4.** Havaldar and others 2023. **5.** Abid, Farooqi and Zou 2021; Caliskan, Bryson and Narayanan 2017; Kaplan and others 2024; Lippens 2024; Nadeem, Bethke and Reddy 2020; Salinas, Haim and Nyarko 2024. **6.** Huang and Xiong 2023; Mexico 2020. **7.** Havaldar and others 2023. **8.** Cao and others 2023. **9.** Chandran 2023; Kirkby-McLeod 2023. **10.** Te Hiku Media 2025. **11.** Pinhanez and others 2023. **12.** Mexico 2020. **13.** Llanes-Ortiz 2023. **14.** Korero Maori 2025; Te Hiku Media 2025. **15.** ITU 2022.

differences carry the risk of incoherence that can stymie innovation, obstruct technological diffusion and ignite races to the bottom.

Regulatory differences can be an opportunity for international cooperation or coordination.[153] International cooperation is even more important for countries with limited ability to influence technology companies' conduct within their own borders. The rationale for international collective action is clear at an intuitive level (digital technologies and their impacts spill across borders, as do their multinational suppliers). But where and how (for instance, cooperation or coordination) need to be specified with more precision.

One recent analysis examined nine policy areas across data, compute and model governance. It concluded that international coordination would yield strong benefits in computer-provided oversight, content provenance, model evaluations (of which benchmarking, discussed in chapter 4, is part), incident monitoring and risk management protocols (table 5.3).[154] Consider the potential for AI audits to ensure that AI development adheres to social, cultural and ethical norms and broadly to the principles of human development (box 5.4). The benefits are lower or mixed for data privacy, data provenance, chip distribution and bias mitigation, as seen from a granular assessment, according to four rationales for international cooperation: cross-border externalities, regulatory arbitrage, uneven governance and interoperability (see table 5.3). Other governance research has highlighted international cooperation opportunities in two broad categories: science and technology research, development and diffusion, and international rulemaking and enforcement.[155]

Table 5.3 Where there is a stronger case for international policy coordination on artificial intelligence

Category	Subcategory	Cross-border externalities	Regulatory arbitrage	Uneven governance	Interoperability	Overall
Data governance	Data privacy	Mixed	Low	Low	Low	Low
	Data provenance	High	High	Low	Mixed	Mixed
Compute governance	Chip distribution	Mixed	Mixed	High	Low	Mixed
	Compute provider oversight	High	High	High	High	High
Model governance	Bias mitigation	Low	Low	Mixed	Low	Low
	Content provenance	Mixed	Mixed	High	High	High
	Model evaluations	High	High	Mixed	High	High
	Incident monitoring	High	Mixed	High	High	High
	Risk management protocols	High	High	High	Mixed	High

Source: Dennis 2024.

Box 5.4 The potential for artificial intelligence audit protocols

International Panel on the Information Environment, Scientific Panel on Global Standards for AI Audits

As artificial intelligence (AI) systems become increasingly ubiquitous across all sectors of society, the need for robust auditing and oversight mechanisms has become more pressing.

Audits offer a way to assess whether the development, deployment and operations of an AI system align with acceptable technical performance, as well as social, cultural and ethical norms and values. Audits can be a critical tool for ensuring that these powerful systems are aligned with the principles of human development—promoting individual freedoms, expanding choices and enhancing the dignity and worth of all people. By rigorously evaluating the development, deployment, management and operations of AI systems, audits can help uncover whether a system engenders individual and collective harms that could undermine core human development objectives. They can help ensure that technical innovation does not pose undue risks to human life or people, guaranteeing that the benefits of AI are equitably distributed and that its risks are mitigated.

At the individual level audits can ensure that AI does not violate fundamental rights and freedoms. Audits assess these systems for fairness, transparency and accountability, protecting individuals from discrimination, exploitation and infringement on their human rights.

Moreover, AI audits can illuminate the broader societal impacts of these technologies, shedding light on how they may inadvertently exacerbate existing discrimination or create new forms of marginalization. By examining the data provenance and supply chains that feed into AI systems, auditors can uncover data colonialism, labour exploitation and environmental degradation—all of which have profound implications for human development.

The International Panel on the Information Environment's Scientific Panel on Global Standards for AI Audits has published two reports to inform policymakers as they develop standards for AI auditing. The first covers existing audit practices and highlights the strengths and weaknesses of different systems currently in operation around the world.[1] The second outlines what a global audit protocol might look like.[2] It gives detailed recommendations for creating a protocol around the auditor, audit object, criteria and evidence, methodology and postaudit activities.

By fostering transparency, accountability and stakeholder engagement, audits can shape AI development in ways that empower individuals, strengthen communities and advance the broader human development agenda.

Notes

1. IPIE 2024. **2.** IPIE 2025.

We are not starting from scratch. International AI initiatives have sprung up—for example, under the auspices of the Global Partnership on AI, the Group of Seven (G7), the International Organization for Standardization, the International Telecommunication Union, the Organisation for Economic Co-operation and Development (OECD) and the United Nations—covering the gamut of data, compute and model governance.[156]

Some have suggested that centralized models of governance may not be best suited for a rapidly evolving technology like AI. Instead, they propose that a distributed network of networks can address the challenges and opportunities of AI governance more effectively than a centralized system.[157] This approach, modelled on the internet, involves a distributed network of governments, industry, civil society and academia addressing AI governance complexities. The G7 exemplifies this approach, serving as a central node in broader governance efforts. Japan's "networked AI" study inspired the OECD's AI ethics recommendations, endorsed by 44 countries.[158] The Global Partnership on AI evolved into an OECD partnership, reinforcing collaborative governance. The Hiroshima AI Process led to a code of conduct and a corporate adherence monitoring function.

In sum, opportunities for international cooperation on AI exist, not necessarily for everything, but certainly for several specific and important areas. In some of them, initiatives are already under way using existing international fora, processes and institutions. New arrangements for AI may be needed, drawing inspiration and lessons from international cooperation—for example, in global health and climate change. We may even need to go beyond centralized arrangements of the past to more distributed and networked architectures that provide flexibility in the face of AI's rapid headline-grabbing advances. Trust, flexibility, trial-and-error—all will be key in carving out an essential and valuable space for cooperation amid a flurry of AI races to generate shared sets of standards and safeguards for healthy competition to steer innovation towards human development and to ensure that everyone has a shot at participating fruitfully in this new AI era.

AI regulation may place new, unique demands on the institutions and agreements underpinning international cooperation. Existing institutions and processes are a good foundation to build on, anchored in the Global Digital Compact.

SPOTLIGHT 5.1

Threats to democratic reason in a high-choice information environment

Åsa Wikforss, *Professor of Theoretical Philosophy, Stockholm University*

Democracy faces unique epistemic challenges in today's digitalized information environment, relating specifically to the capacity to make rational, knowledge-based decisions. Democracies have unique epistemic strengths that allow them to solve complex problems and build better societies.[1] Democratic governance exhibits a form of collective intelligence, a "democratic reason," that is not exhibited by nondemocratic modes of governance. While there is great diversity among the world's democracies, including low- or high-functioning electoral and liberal democracies, a distinctive trait in all of them is that they exhibit certain epistemic strengths.[2]

The digital information environment poses a set of distinct threats to democratic reason. In a world facing a set of interconnected crises, epistemically well-functioning democracies can support knowledge-based and rational policymaking. Moreover, the weakening of democratic reason poses a danger to democracy itself.

The value of democracy

Democracy has not only an important procedural value but also an important substantive value, relating to the actual outcomes of democratic decisionmaking.[3] Empirical studies show that democracies tend to produce outcomes that are generally considered good: they tend to avoid calamities (such as famines and wars), enhance human wellbeing along several dimensions (for instance health, life expectancy, equality and happiness), provide better protections for the environment and are better at dealing with crises (such as a pandemic).[4]

The epistemic argument for democracy is that democratic decisionmaking is uniquely equipped to be rational and knowledge based. Democracies have these epistemic strengths due to the ability to harness collective intelligence through two essential mechanisms: majority rule and deliberation. Majority rule enables democracies to harness the wisdom of crowds, and deliberative democracy facilitates public reasoning through respectful, open dialogues to reach consensus. For instance, in a representative democracy, while parliament plays a central role as a deliberative forum, an open and fair public debate is also essential, both when it comes to providing knowledge-based decisions and for securing the legitimacy of these decisions.[5]

The main critic of the epistemic argument for democracy is that it relies on assumptions that may not be true. For example, the assumption that voters have knowledge about politically relevant facts, such as climate change, existing policies or consequences of prior political decisions[6]. Naturally, voting behaviour is a reflection not simply of the factual beliefs that voters hold but also of their values. Nevertheless, voters' factual beliefs are a key psychological factor underlying their behaviour, and if voters are ignorant or mistaken in these factual beliefs, it will have consequences for how well democracy works. To what extent does the information environment pose a threat to the epistemic strengths of democracy? How does this affect the capacity of democracies to address key global challenges?

A high-choice information environment

Scholars describe the changed information environment as a transformation from a low-choice to a high-choice information environment. This has consequences for the use of and trust in media. People's individual motivations and abilities become key determinants in what information they consume,[7] further increasing the risk of biases. The demand for information that merely confirms (rather than informs) people's views affects their trust and use of established news media. The design of social media platforms, where algorithms promote content that captures people's attention, potentially compounds this challenge. The complex interaction between empirical beliefs and attitudes of trust can exacerbate polarization of media trust, often along political fault lines. Polarized trust in turn causes factual belief polarization, where political opponents hold opposing beliefs on empirical facts. Research shows that factual belief polarization can occur simply as a result of selective sharing patterns in digital ecosystems.[8] Similar polarization effects can be seen when it comes to trust in science.[9] Partisanship therefore both drives media trust and is driven by media use, leading to an increasingly partisan media landscape.

It should be stressed that misinformation and disinformation not only lead people to hold false beliefs about the world but also undermine our capacity to critically assess further information that we receive. Evaluation of the plausibility of a piece of information is always carried out against the background of our prior beliefs. If these beliefs, in turn, are the result of unreliable sources, the resulting assessments will be equally unreliable. For instance, for someone who has been fed disinformation about climate change, additional disinformation will seem plausible. Indeed, given a person's acquired, false background beliefs, it may even be rational (from the subject's point of view) to reject the testimony provided by expert consensus on anthropogenic climate change.[10]

The role of prior beliefs in assessing information highlights the fact that efforts to counteract disinformation and misinformation at the individual level, such as debunking, while important, have limitations.[11] In a polluted information landscape people's critical thinking capacities may be compromised.[12] Efforts to strengthen these critical thinking skills will have to be combined with initiatives to improve the quality of the information environment—for instance, by having social media platforms amplify reliable information, making it easier for people to fact check and track truth. In a recent survey a majority of experts stressed the importance of supporting free and independent media.[13]

Harms to democratic reason

The transformation of the information environment has consequences for central mechanisms underlying the epistemic potential of democracy: aggregation and deliberation. In a high-choice information environment, with large amounts of unreliable information and where biases and background beliefs determine both the assessment of new information and the choice of who to trust, there is a very real risk that large groups of individuals will do worse than chance. If the evidence presented to a population is systematically misleading, the majority of people will be systematically misled. If so, a central condition for Condorcet's jury theorem will not be met. Moreover, systematic disinformation in combination with systematic biases, reinforced by increased partisanship, means that errors will not be random and may not cancel out.[14]

The high-choice information environment also poses risks to the deliberative dimension of democracy. Policy disagreements always have two potential sources: disagreement on values and disagreement on the facts. People may disagree on a given climate policy because they disagree on the value of mitigating climate change, in particular when such mitigation conflicts with other things they value (such as lower gas prices). But they may also disagree on the underlying climate science. A central function of democratic deliberation is to assess the arguments on either side, relating to both facts and values, exposing poor reasoning and weeding out falsehoods. Under ideal circumstances the end result is some form of consensus. But even when consensus is not achieved, deliberation allows for a peaceful management of disagreement, helping people understand different points of view and paving the way for political compromise. The idea that well-structured deliberation can be effective is borne out by the application of deliberative mini-publics across the world, where a representative assembly of citizens deliberates on topics relevant to policymaking.[15] Examples include citizens' assemblies both at the local level (involving deliberations about local budget decisions, for example) and at the national and transnational levels, where topics such as climate policy, constitutional reform and a variety of social issues have been discussed.

Mini-publics are designed to increase public participation and have been shown to counteract belief polarization and strengthen knowledge-based decisionmaking. Similar results can be seen from experimental work on deliberative polling, which involves examining how people's political views are affected by group deliberations where trained moderators and dialogue with experts are included.[16]

In the new information environment, however, reaching consensus through public deliberation is increasingly difficult, considering that a distinctive feature of the current era is increasing disagreement on facts and the interpretation of data.[17] When deliberation is based on false and misleading information, the "reasons" provided will not be truth-conducive, and the possibility of reaching a knowledge-based consensus is compromised. This also harms the epistemic function of deliberation, when it is weaponized to generate epistemic cynicism, causing people to devalue contributions from reliable sources.[18] Relatedly, politically polarized trust in media and science poses a serious obstacle to finding a common ground of empirical facts. And increasing, unbridgeable factual disagreements, in turn, will cause increasing, unbridgeable political disagreements.

This is related to concerns about knowledge resistance, the tendency to resist available knowledge. Knowledge resistance involves a form of response to available evidence, where belief formation is driven by desires rather than by the evidence.[19] Thus, in the case of tribal thinking, there is the desire to hold on to beliefs that have become a mark of identity of the group—for instance, beliefs about vaccines or about genetically modified organisms. In such a situation, the fear of being excluded from the group causes people to resist available evidence that the belief held is false. A prominent psychological mechanism driving knowledge resistance is motivated reasoning, the tendency of individuals to unconsciously conform assessment of factual information to some goal collateral to assessing its truth. In the case of politically motivated reasoning, involved in tribal thinking, evidence is assessed based on its congeniality to the position associated with our particular political or cultural affiliations.[20] Thus, evidence against the belief held by the group is undermined.

Knowledge resistance interacts with the high-choice information environment in complex ways. Rationalizing a cherished belief in the face of counterevidence often involves trying to find reasons not to trust the relevant source of the evidence. For instance, when there is (near) expert consensus, as in the case of anthropogenic climate change, resisting the expert testimony typically involves adopting a conspiracy theory.[21] The availability of conspiracy theories in the digital information environment thus serves to strengthen the type of motivated reasoning involved in science denialism.

Conclusion

In sum, the new high-choice information environment, engendered by the digitalization of information, poses a serious threat to the epistemic strengths of democracy. First, it undermines the conditions required for truth to emerge from the aggregation of opinions. Second, it weakens democratic deliberation and the possibility of resolving disagreements by appealing to evidence and rational arguments. With the emergence of generative artificial intelligence tools, systems capable of creating texts, images and videos with astonishing speed and facility, scholars worry that the quality of the information environment could deteriorate further.[22]

Much work is currently being done to understand and address these epistemic threats to democracy, but there are many barriers to such research.[23] A central problem, among others, is poor access to data; legislation demanding greater transparency on the part of technology platforms is essential, such as the EU Digital Services Act. Upholding academic freedom for information scholars is key for the future of the research field.

NOTES

1 See especially Goodin and Spiekermann (2018) and Landemore (2012).

2 See the classification employed by the V-Dem Institute, where five high-level principles of democracy are distinguished: electoral, liberal, participatory, deliberative and egalitarian (V-Dem Institute 2025).

3 For a clear articulation of this reasoning, see Landemore (2012).

4 Lundstedt and others 2022.

5 See, for instance, Habermas (1984) and Landemore (2012).

6 Brennan 2016.

7 Aelst 2017; Strömbäck and others 2022.

8 Bowen, Dmitriev and Galperti 2023.

9 For a discussion of polarization and trust in science, see Rekker (2021).

10 Glüer and Wikforss 2022; Levy 2021.

11 For a useful guide to interventions against misinformation on the individual level, see Kozyreva and others (2024).

12 Wikforss, Kendeou and Robinson 2019.

13 International Panel on the Information Environment 2024.

14 Goodin and Spiekermann 2018.

15 See, for instance, Escobar and Elstub (2017), Participedia (2025) and Smith (2009).

16 See Stanford Deliberative Democracy Lab, where more than 150 deliberative polling experiments have been run in more than 50 countries.

17 Rich 2018.

18 McKay and Tenove 2021.

19 Glüer and Wikforss 2022.

20 Kahan 2015.

21 Lewandowsky, Gignac and Oberauer 2013.

22 International Panel on the Information Environment 2024.

23 International Panel on the Information Environment 2024.

CHAPTER

6

Reimagining choices: Towards artificial intelligence–augmented human development

Reimagining choices: Towards artificial intelligence–augmented human development

Seizing the opportunities of AI demands more than technological innovation. Bridging micro- and macro-level evidence, this chapter proposes an actionable framework for artificial intelligence (AI)–augmented human development that is robust to fast-paced technological change. It outlines three directions for action: building a complementarity economy, driving innovation with intent and investing in capabilities that count. Together, these directions aim to inspire context-specific choices so that countries can harness AI to expand opportunities, enhance people's capabilities and deliver improvements in people's lives.

Scientific and technological progress propel development[1] while changing patterns of economic opportunity and redrawing inequalities.[2] As artificial intelligence (AI) moves from a niche technology to a cornerstone of people's lives across multiple domains, how can we seize its potential to advance human development?[3]

The answer depends on more than just algorithms. We cannot code away complex social problems or deploy AI based on wishful and simplistic approaches.[4] New fault lines may have less to do with the dichotomy between humans and AI and more to do with the difference between humans capable of leveraging AI versus humans without those capabilities. Rather than trying to predict where those fault lines lie, this chapter explores choices to shape our future with AI to advance human development.

The chapter bridges micro- and macro-level evidence and analysis to put forward a framework for AI-augmented human development. Detailed policies and interventions need to attend to both the context in which AI is deployed and its affordances,[5] so the chapter outlines three strategic directions to inform more detailed actions: building a complementarity economy, driving innovation with intent and investing in capabilities that count. These three directions aim to inspire choices for AI-augmented human development that unleash a virtuous cycle between AI innovation and deployment and outcomes that improve people's lives.

- *Building a complementarity economy.* Choices that build a complementarity economy include those that make AI pro-worker through institutions and policies that empower workers to use AI to augment what they do while limiting AI curbs on worker agency. Those institutions structure incentives and regulations that foster the complementarity between labour and AI.[6] Doing so implies recognizing AI's comparative advantages over earlier digital technologies—its adaptability and generative capacities, as well its widespread accessibility and relative ease of use through features such as natural language processing, which provide unique and novel opportunities.

  But it also implies understanding what AI cannot do—or cannot do better than either humans or other digital technologies. A complementarity economy hinges in part on avoiding AI deployed as "so-so technology" that merely mimics what people do—automating work but resulting in job losses without delivering broader productivity gains.[7] Instead, AI designed to augment human work can enhance productivity, support economic diversification and speed up technological progress.[8] AI's potential to create positive spillovers across economies depends on networks comprising humans and AI—AI alone will not realize that potential because its adaptation to unique and varied contexts often requires human steering and evaluation (chapter 1). Where access to advanced expertise is limited, AI-powered tools can bridge gaps and enable workers to perform higher-value tasks.[9] This may enhance economic opportunities, including for those historically left behind.[10]

  Because AI runs on existing physical infrastructure, the transition to a complementarity economy may not require extensive new physical investment, as long as electricity and internet access (including over time broadband and cloud computing services) is ensured (chapter 1, spotlight 6.2).
- *Driving innovation with intent.* Choices should be geared to harness AI's potential to accelerate science and technological innovation, not by automating creative processes but by augmenting them, building on the distinct complementarity between humans and AI.[11] This includes leveraging AI to expand what people can do as we continue to seek to fulfil those fundamental human aspirations to understand and create, reflected in activities ranging from basic science to the arts. Thus, AI should not be measured solely by its potential to replicate what humans can do to improve automation but also by its ability to enhance human capabilities. That should inspire research and technological efforts that drive the evolution of AI itself.[12] Adjusting economic incentives and expanding AI benchmarks beyond performance and safety to include how AI can advance human development can help align socially desirable and privately profitable innovations. For example, AI can accelerate efforts to tackle planetary challenges, such as biodiversity loss and climate change (spotlight 6.1).[13] Crucially, human agency must remain central to AI design, development and deployment.[14]
- *Investing in capabilities that count.* Choices should be geared towards both investing in human capabilities and leveraging AI to enhance access and

quality of education and health service delivery. AI's flexibility and adaptability should be leveraged to personalize education and healthcare in different development settings while attending to risks and concerns with bias, privacy and equity.[15] By tailoring learning or expanding healthcare, AI can also generate demand for complementary human labour.

When integrated into education, AI should not be used as a crutch by teachers or students but as a companion to unleash new ways of learning that allow us to move the focus beyond increasing years of schooling (quantity) towards achieving basic numeracy and literacy skills and developing critical, creative and relational thinking (quality). This involves deploying AI to scale up interventions known to enhance education outcomes, such as customized learning, rather than deploying it for its own sake. In healthcare AI should be deployed to complement healthcare expertise—particularly when such experience is scarce—empowering healthcare workers to do more.[16] Healthcare systems and organizations should ensure safe and transparent integration of AI technologies into services—strengthening both institutional and frontline providers' capacity to effectively use these new tools while clearly communicating to patients how AI is employed in clinical decisionmaking. Because the unintended side effects of AI in health services may change over time, monitoring AI biases and health inequalities needs to be seen as a continuous process.[17]

The pursuit of these three directions will have to take account of unfolding structural shifts in the global economy[18] that are reshaping development opportunities (chapter 1). AI holds promise for expanding development trajectories, but it could also amplify risks if it becomes a source of fragmentation that compounds geopolitical tensions and regulatory divergence, forcing countries to align with one approach or another, undermining cross-border cooperation. Global disparities in the AI supply chain would then deepen inequalities across countries, especially if low and medium Human Development Index (HDI) countries are excluded from the supply side of AI (chapter 5). Pre-existing development gaps in electricity and internet access, and in basic learning capabilities, can be major barriers to seizing the opportunities of AI-augmented human development.

> "By reimagining choices, we can shift the conversation from if and when AI can replace humans to how AI can enhance human potential and foster human development

What matters is not predicting what will happen but making choices so AI advances human development. AI is distinctive in its economywide applicability,[19] swift diffusion[20] and growing opportunities for levelling the playing field in accessing advanced expertise (chapter 1). Seizing these opportunities depends on how AI is designed and deployed, as well as the business models and incentives that shape its use. The role of AI in shaping our societies depends on choices. By reimagining choices, we can shift the conversation from if and when AI can replace humans to how AI can enhance human development.

Building a complementarity economy to expand development frontiers

History has shown that occupations evolve and that new occupations emerge as new technologies diffuse across the economy.[21] But the speed and scope of AI integration into our economies[22] may pose novel challenges and opportunities. AI does not have to be a zero-sum game that pits humans against machines. Policy choices can shape a "complementarity economy," where AI amplifies the work humans are already doing,[23] supports inclusion in labour markets[24] and breaks open entirely new types of industries, jobs and tasks.[25] Realizing these gains requires understanding how technological change interacts with underlying labour market and economic structures and how AI differs from previous digital technologies.

In a complementarity economy, automation—AI replacing human work—and augmentation—AI boosting productivity and driving creation of new types of roles for human workers—happen in parallel. Policies that tilt the balance towards augmentation are key while supporting people as they navigate disruptions in the world of work.

People expect AI to change existing occupations and create new ones

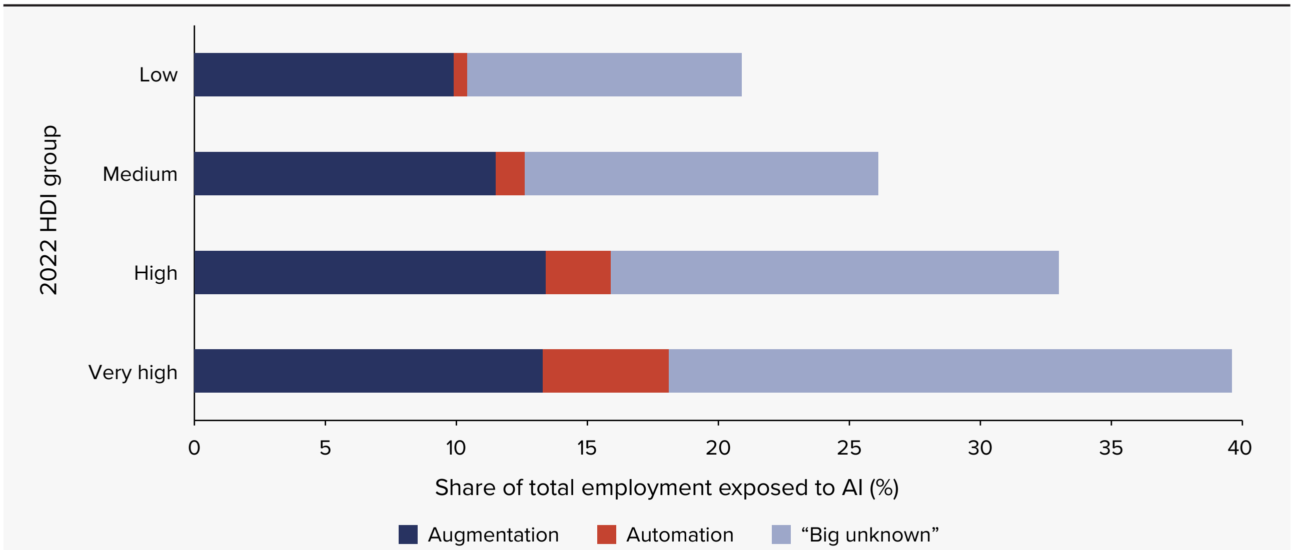
For many of the reasons outlined in chapter 1, new economic opportunities with AI may outweigh automation and replacement, if labour-enhancing incentives and policies are put in place. Data on job exposure to AI seem to confirm this (figure 6.1). Across HDI groups the augmentation exposure of current employment is higher than the automation exposure. Female employment shows higher job exposure to AI augmentation than male employment.[26] However, the largest share of jobs exposed to AI falls into "a big unknown," with potential for both augmentation and automation. Whether these roles will ultimately be augmented or automated is contingent on future technological progress and the choices made in response to those changes—presenting a major opportunity to shape the future of work in ways that could benefit workers and spur innovation and productivity.

However, exposure does not necessarily imply that people are using AI for work.[27] Our survey points towards an expected increase in use of AI tools for work, even though a substantial share of people are still not using them (figure 6.2). Men and people with greater levels of education report higher use of AI for work—across all HDI groups, highlighting the need for targeted policies to ensure that women and people with lower levels of education also benefit from labour-enhancing AI opportunities.

According to our survey, about half of respondents expect AI to lead to job automation. But an even larger share, 60 percent, expect new opportunities for job augmentation to arise. People in low and medium HDI countries have higher expectations of shifts in the labour market than people in very high HDI countries (figure 6.3). In low and medium HDI countries 70 percent of respondents expect that AI will help them increase their productivity at work, and 64 percent expect that AI will help them find new job roles that currently do not exist, while 57 percent expect that their current jobs will be replaced due to AI.

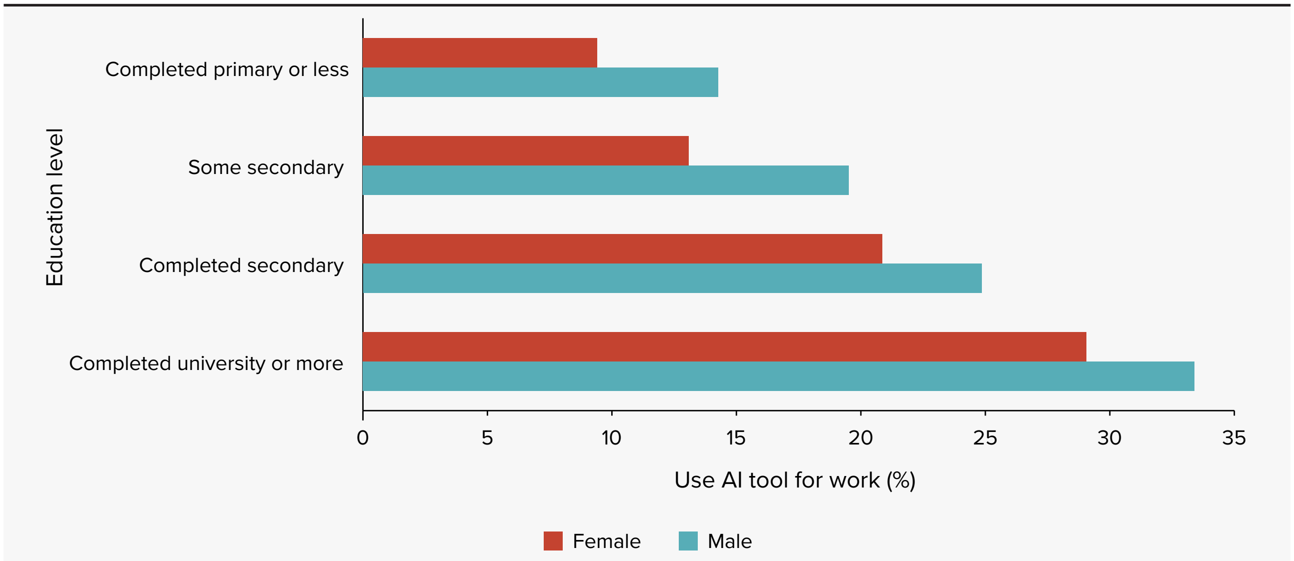
AI's ability to carry out work once thought of as exclusively in the realm of humans—such as complex cognitive or creative tasks—is now challenging the belief that automation technology affects mainly lower-skill workers engaged in routine tasks.[28] However, our survey results show that while respondents expect automation to take place across occupations, they also expect augmentation to occur (figures 6.4 and 6.5). Almost 40 percent of clerical workers—an occupation that is typically portrayed as being at risk of AI automation—expect that AI will lead to transformational change of their jobs and perceive both

Figure 6.1 Across Human Development Index (HDI) groups the largest share of jobs exposed to artificial intelligence (AI) falls into "a big unknown"



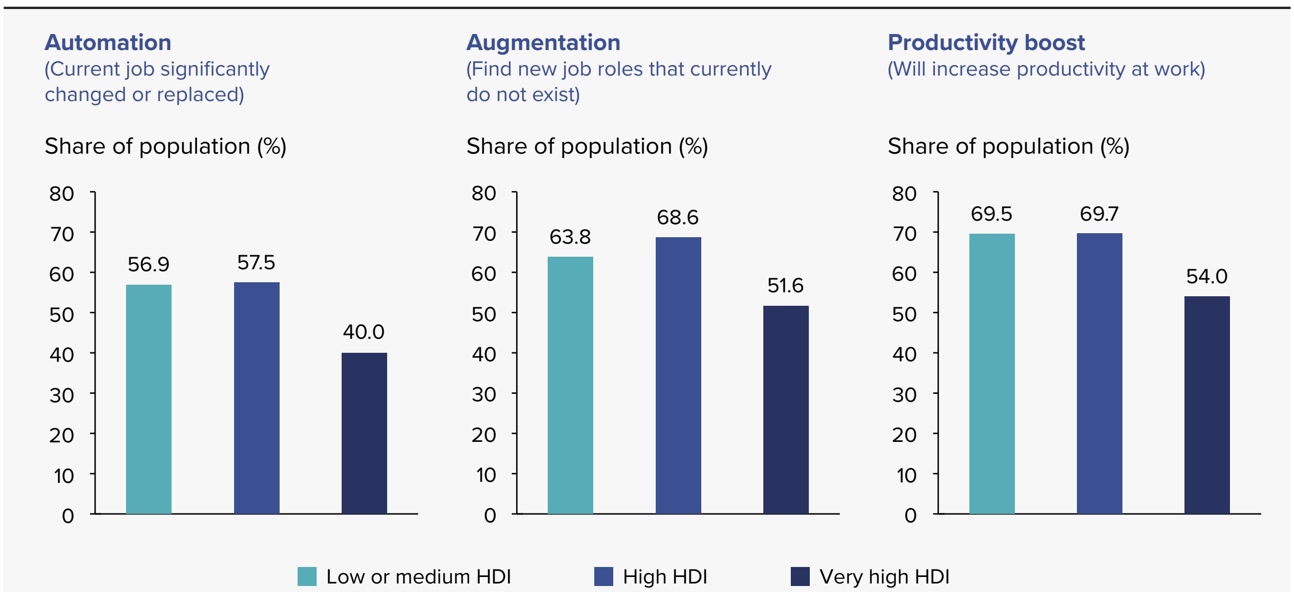
Source: Human Development Report Office using data from the International Labour Organization Harmonized Microdata Repository and the method described in Gmyrek, Berg and Bescond (2023).

Figure 6.2 Men and people with greater levels of education report higher use of artificial intelligence (AI) for work—across all Human Development Index groups



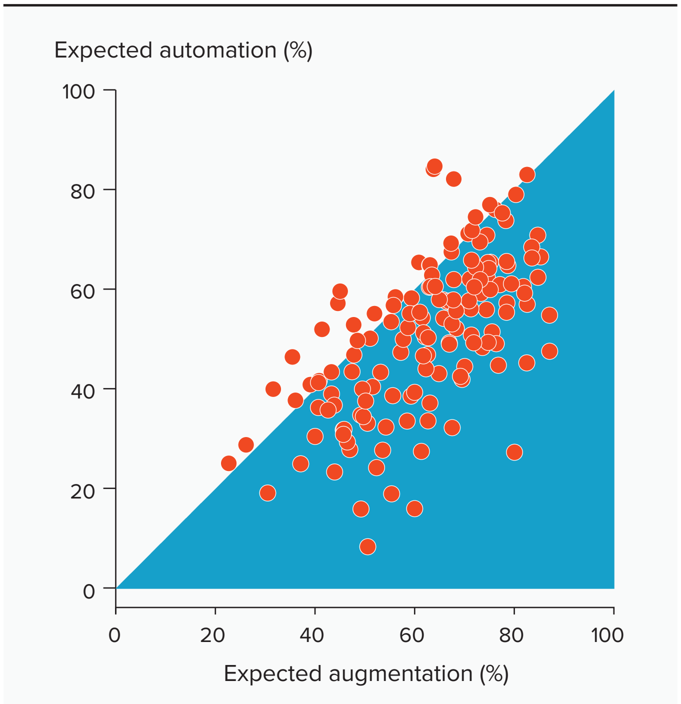
Note: Based on pooled data for 21 countries. Use of AI for work refers to the responses to the question "In the past 30 days, have you interacted with artificial intelligence, such as chatbots, in any of the following ways? Work-related tools or software."
Source: Human Development Report Office based on the United Nations Development Programme Survey on AI and Human Development.

Figure 6.3 More respondents in low and medium Human Development Index (HDI) countries expect labour market changes—through augmentation, automation and productivity boosts—with artificial intelligence



Note: Based on pooled data for 21 countries. Expected effects of AI on jobs refer to the percentage of respondents who answered "very likely" or "likely" to the questions "Your current job will be significantly changed or replaced by AI" (automation), "AI will help you find new job roles that currently do not exist" (augmentation), and "AI will increase your productivity at work" (productivity boost), as well as 50 percent of the respondents who answered "neutral."
Source: Human Development Report Office based on the United Nations Development Programme Survey on AI and Human Development.

Figure 6.4 **Across occupations and Human Development Index levels, respondents expect that artificial intelligence will both automate and augment their work—with higher expectations of augmentation**



Note: Based on pooled data for 21 countries. Each dot represents the percentages of respondents in an occupation group in a country who expect automation and augmentation from AI to affect their occupation. The following occupational groups are used: professional/higher administrative, skilled, unskilled/semi-skilled, services, clerical, farm and other. The shaded area represents a higher share of respondents expecting augmentation than automation.
Source: Human Development Report Office based on data from the United Nations Development Programme Survey on AI and Human Development.

augmentation opportunities and automation risks) (figure 6.5). Overall, 4 of 10 respondents expect to be affected by both augmentation and automation, so while they believe that their current jobs will be substantially changed by AI, they also expect that AI will create new job roles that do not currently exist.

New economic possibility frontiers—avoiding "so-so" technology

Despite rapidly expanding AI use, macro-level productivity impacts remain elusive:[29] today, AI seems to be "everywhere but in the productivity statistics."[30] There are several reasons why this might be the case. Estimates of job exposure to AI vary substantially,[31] the translation from AI job exposure to AI use and from AI use to productivity impacts is not straightforward and current systems of national accounting have a hard time capturing quality improvements from technologies, as well as the effects of services, especially digitally delivered services, which account for an increasing share of employment and value added.[32] So how to assess the economic potential of AI? Rather than making predictions, examining the mechanisms through which it can drive change and identifying where these effects might emerge provide a more nuanced understanding that can support better-informed decisionmaking (box 6.1).[33]

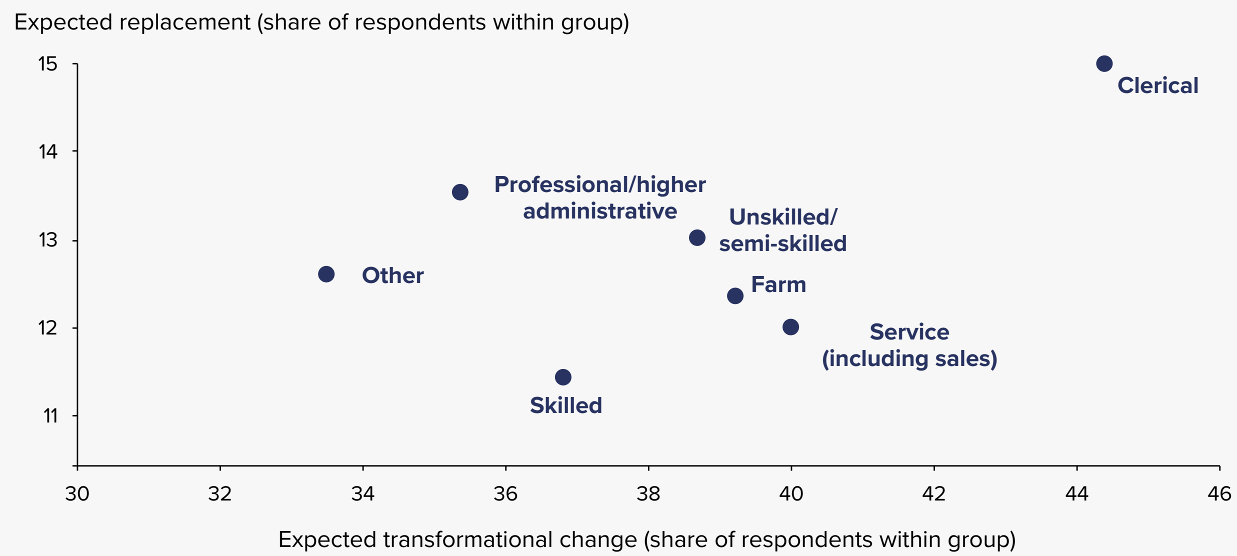
Unlike technologies narrowly focused on a specific activity or task, AI—and particularly generative AI—is more akin to a general purpose technology in that it has economywide applicability[34] and may affect more and more tasks.[35] Multimodality, adaptability and generalizability are key features of novel AI systems, and use cases already range from economics research assistance[36] to medical image analysis for early disease detection[37] and from customer service support[38] to helping with novels or screenplays.[39]

AI presents multiple opportunities for augmenting what people are already doing at work. It can help workers complete tasks faster and at higher quality,[40] boost their creativity[41] and speed up learning processes, raising productivity for newer recruits and those with lower performance.[42] Beyond the direct effects associated with more productive execution of tasks currently done by workers, the more far-reaching economic potential of AI may lie in its second- and third-order effects—in its potential for spillovers and its integration with technological progress.[43]

These economic spillovers and dynamic effects can drive productivity gains beyond those achieved through pre-AI digital tools, potentially fostering novel industries and value chains, if regulatory frameworks ensure fair competition and prevent rent-seeking behaviour.[44] Without such safeguards market concentration may stifle innovation,[45] inflate prices and concentrate productivity gains among a few dominant players. If AI functions primarily as a "so-so technology"[46]—delivering cost savings for individual firms without driving broader productivity gains—its potential to expand economic opportunities and enhance innovation may be limited.[47]

Prioritizing AI as an enabler for innovation and intelligence augmentation is likely to yield far more benefits than focusing on automation alone.[48] Balancing policies that caution the use of AI with those

Figure 6.5 Across occupations respondents expect transformational change to their work



Note: Based on pooled data for 21 countries. Each point represents the expected replacement (automation with no augmentation) and transformational (automation and augmentation) change for an occupation group.
Source: Human Development Report Office based on the United Nations Development Programme Survey on AI and Human Development.

Box 6.1 Assessing artificial intelligence's productivity effects

Artificial intelligence (AI) is expected to yield considerable productivity impacts, but empirical findings remain inconclusive.[1] The magnitude, timing and distribution of productivity effects are uncertain and depend heavily on the methodology and assumptions.[2] The US National Academies of Sciences, Engineering and Medicine has proposed a framework for assessing AI's productivity effects by identifying key factors that may shape its impact.[3] The factors provide a helpful overview of the conditions that influence AI adoption, the channels through which AI can affect productivity and the potential barriers to realizing its full economic impact.

They include:

- *Share of the economy in which the technology can be applied and size of the productivity effect in those applications.* This follows from Hulten's theorem, which shows that in well-functioning economies an increase in total factor productivity in one industry will change the overall output in an economy in proportion to the industry's share of total sales.[4] AI is seen as a general purpose technology; it has economywide applicability beyond specific industries.[5] The productivity effects in particular industries, by contrast, depend on whether AI primarily replaces humans or augments what humans are doing.[6]
- *Complements and bottlenecks.* Deploying a new technology without considering parallel investment would likely yield disappointing results. Workers need complementary skills,[7] and firms and organizations may need to adjust workflows to fully leverage AI. Digital infrastructure is critical, and targeted investment may be needed in many regions.[8] Furthermore, governance frameworks might require time to adjust to new technologies. Informal institutions, such as those for social cohesion and trust, can also act as complements or bottlenecks to realizing the technology's potential.[9]
- *Time lags and measurement.* Both benefits and costs from technological innovation may be hard to quantify, especially for a general purpose technology. Some AI-driven benefits, such as enhanced learning through personalized tutoring (at low cost), might not show up in productivity statistics at all or only after a considerable time lag.[10] Productivity gains often take time, as economies, firms and workers adapt, bottlenecks are addressed and complementarity investments are made. However, AI's productivity impacts may materialize faster than those in

(continued)

previous waves of technological innovation. AI's adaptive and learning capabilities, decreasing costs of computing and the fast-paced adoption across the world may all shorten the time lag between innovation and productivity.[11] Generative AI in particular is spreading faster than earlier technology, such as the internet or the personal computer.[12]

- *Economic spillovers.* Both the benefits and costs of technological innovation can spill over from the private innovator to other parts of society. AI, with its many use cases, may have large impacts through these spillovers. For example, improving medical diagnosis[13] can have positive spillovers to public health, while negative spillovers such as rent seeking or widespread AI-generated misinformation could distort markets and limit AI's economic potential.[14]
- *Heterogeneity within and across businesses and sectors.* The extent to which AI enhances productivity in a sector or for a firm is contingent on industry dynamics and firms' adaptability and technological readiness. For example, sectors with high digital penetration may have an easier time integrating AI applications and driving productivity gains. Firms able to adapt organizational structures and workflows to AI and leverage AI for product innovation may see higher growth[15] than those slower to adapt. Disparities within firms may arise between workers who are able to leverage AI to augment their work and workers who struggle to integrate it into their work or see large parts of their tasks displaced.
- *Dynamic effects.* Beyond spillovers AI's third-order effects include the potential to accelerate innovation and scientific discovery, key contributors to productivity gains. By processing vast amounts of data and identifying patterns[16] or by automating time-consuming tasks and enabling people to focus on higher-order problem solving and creativity, AI could greatly increase the pace of new breakthroughs, reshaping long-term productivity trajectories.

Notes

1. Comunale and Manera 2024. **2.** Berg and Gmyrek 2024. **3.** National Academies of Sciences Engineering and Medicine 2024. **4.** Hulten 1978. **5.** Crafts 2021. **6.** Acemoğlu and Restrepo 2019. **7.** UN and ILO 2024. **8.** World Bank 2024. **9.** Antonietti, Burlina and Rodriguez-Pose 2025. **10.** Coyle 2025. **11.** Crafts 2021. **12.** Liu, Wang and Zhenwhei Qiang 2024. **13.** Wang and Preininger 2019. **14.** Fallis 2021. **15.** Babina and others 2024. **16.** Mullainathan and Rambachan 2024.

geared to using AI can unlock productivity and open new possibility frontiers.[49] The net effect of the AI revolution on economies is likely contingent on countries' "ability to innovate, adopt and adapt to AI."[50] For low- and middle-income economies it can present a major opportunity for economic diversification[51] by lowering barriers to access to advanced expertise (chapter 1), enabling and streamlining trade[52] and improving service delivery in education, healthcare and other public services, in addition to enabling financial inclusion.[53] This requires investment in infrastructure, workforce training and inclusive digital ecosystems (box 6.2).

Seizing on the complementarity between AI and people

A critical determinant of AI's productivity impact is the degree to which it can be applied across economies.[54] Countries with different sectoral compositions, institutional capacities and workforce skill compositions may experience AI's diffusion and impact in different ways, and complementarity strategies need to be attuned to context. Currently, higher-income economies with greater digitalization and a workforce more accustomed to using digital tools may be better positioned to harness AI.[55] For example, in Latin America a substantial share of workers who are employed in jobs that could benefit from AI do not have access to or are not using computers in their day-to-day work—limiting the potential of AI augmentation.[56]

So, how to steer towards complementarity? Workers' agency and influence—directly in their work and through social dialogue—have to be part of a broad package of policies that prioritize investment in human–machine collaboration.[57]

Fiscal policy shapes economic incentives and can direct investment in research and development, as well as how firms adopt AI. While the impact of AI on productivity across workers is not completely straightforward, and implications for wage distribution remain uncertain, digital technological

Box 6.2 Smart systems, shared goals: The complementarity of artificial intelligence and digital public infrastructure

Traditionally, infrastructure has been associated with physical assets such as roads, electricity grids and water systems that provide essential services for public use. Digital public infrastructure is a multidimensional approach to national digital transformation that relies on both physical and virtual systems. At its core, digital public infrastructure is about building and managing digital systems that support essential services in today's society. These systems include proving one's identity online, sending money quickly and securely and sharing information safely—with the right privacy protections and consent.[1] Services aim to be inclusive so no one is left out, foundational so others can build on them, interoperable through open standards that can support diverse uses and publicly accountable to ensure they serve the public interest rather than private or siloed goals.[2]

Digital public infrastructure can speed up the use of AI. Many AI applications need both unstructured and structured data. Structured data often come from different government registries and databases, which are usually spread across ministries, departments and agencies. For example, in India AI is helping farmers get real-time support, including access to insurance and subsidies in their local languages—something that depends on combining many different data sources.[3]

AI can enhance digital public infrastructure. Unlike traditional infrastructure, digital public infrastructure is highly scalable, adaptable and reusable, offering unprecedented innovation potential. For instance, Stripe—a global payments platform—uses machine learning to spot signs of fraud by analysing unusual transaction patterns, shifts in purchasing behaviour and changes in device details.[4] Similarly, AI powers biometric authentication in digital ID systems, which is especially useful where fingerprint recognition does not work well. This approach has been promoting inclusion, as, for example, many agricultural and manual workers face fingerprint erosion, making alternative biometric methods more reliable.[5]

Despite the growing potential, research on the causal links between digital public infrastructure and AI remains limited. More work is needed to understand how these two concepts can reinforce each other, what risks their interaction may pose and how policymakers should approach their integration, ensuring that benefits are widely distributed and reinforcing human agency, trust and fairness in the digital age.[6]

Notes

1. Eaves and Sandman 2021. **2.** Eaves, Mazzucato and Vasconcellos 2024. **3.** D'Silva and others 2019. **4.** Adams 2025. **5.** Digital public infrastructure can be vulnerable to serious threats, such as disinformation campaigns that undermine public confidence. A notable example comes from Brazil, where false information about a new regulation related to Pix—an instant digital payment platform—circulated widely, impacting more than 9.4 million people in 2025 (Luciano and Fleck 2025). **6.** Rikap 2024.

advancements have tended to be accompanied by larger capital investment and higher capital shares of income.[58] The relevant lens for tax policy may thus involve rebalancing capital and labour taxation to equitably distribute productivity gains and encourage investment in labour-complementing technology.[59] The design of such taxation matters and should be carefully considered. For example, while taxing specific technologies—for example, a "robot tax"—may hamper innovation in a particular field,[60] broader instruments such as capital income tax may achieve both efficiency and equity.[61]

AI itself can be leveraged as a tool for improving tax revenue by enhancing compliance and increasing administrative efficiency. AI-driven tools can help governments monitor complex financial transactions, detect fraud and reduce evasion.[62] Strengthening tax systems is important for developing economies, which struggle with closing tax revenue gaps and increasing the tax-to-GDP ratio beyond 15 percent—a threshold associated with positive effects of taxation on economic growth and development.[63] Expanding fiscal space through improved revenue collection can in turn fund critical complementarity investment—in education, skills development and digital infrastructure.

Beyond taxation public investment in research and development of labour-enhancing AI, along with strategic subsidies for firms to adopt these types of technologies, can tip the balance towards AI as an enabler for augmentation and innovation.[64] Public–private partnerships can drive labour-enhancing AI innovation and bridge gaps between research and development, business cases and societal needs (see box 6.4 later in the chapter). For example, in Mexico a newly established private sector–academia collaboration, GenAI Laboratory, is connecting research, education and real-world AI-applications.[65]

Investing in complementarity implies establishing a level playing field in economies and enabling firms of all sizes and across all sectors to engage in the AI economy.[66] In many places this starts with closing digital divides and enabling universal and meaningful connectivity (spotlight 6.2). Robust high-speed internet networks serve as the backbone for implementing more advanced digital tools,[67] but governments can go further by advancing and integrating AI into digital public infrastructure (see box 6.2). Publicly accessible AI infrastructure—such as shared computing resources, open source AI models and publicly curated datasets—can democratize AI development and adoption. Furthermore, well-designed competition policies can foster a competitive and dynamic technological ecosystem that drives innovation and ensures that AI-driven gains are broadly distributed rather than concentrated among a few dominant players.[68]

> "Publicly accessible AI infrastructure—such as shared computing resources, open source AI models and publicly curated datasets—can democratize AI development and adoption. Furthermore, well-designed competition policies can foster a competitive and dynamic technological ecosystem that drives innovation and ensures that AI-driven gains are broadly distributed rather than concentrated among a few dominant players

Fast AI diffusion and adoption can be disruptive because overall workforce skill composition may take time to adjust. Vocational programmes that are adaptive and aligned with emerging industry needs can bridge skills gaps quickly and improve employment prospects,[69] while on-the-job training and upskilling may support those whose jobs and tasks are reshaped by AI.[70] Public–private partnerships and other multistakeholder alliances can support learning systems that remain responsive to the evolving demands of an AI-driven economy and bridge gaps between formal education, vocational training and industry needs.[71] For example, initiatives such as the Organisation for Economic Co-operation and Development's (OECD) Skills for Jobs database offers up-to-date information about the types of expertise in demand across sectors and regions.[72]

AI might reshape demand for different types of expertise. By increasing access to advanced expertise, it may make some types of specialized knowledge less exclusive while raising demand for others (chapter 1). The implications for developing economies are particularly important. Where access to advanced expertise has historically been limited, AI-powered tools could bridge gaps in education, healthcare and financial services and enable workers to perform higher-value tasks with less formal training.[73] For example, in some parts of Kenya, Nigeria and South Africa, AI solutions are enabling smallholder farmers to engage in precision agriculture, optimizing resource efficiency, enhancing yields and reducing environmental harms.[74]

However, as AI reshapes the demand for expertise, some jobs may see less demand while new ones are created. New roles might not require the same types of expertise or might emerge in a different sector or place from where job losses occur.[75] Robust social protection systems, along with active labour market policies, can mitigate income losses and help people navigate shifting work demands.[76]

Including workers in AI gains and governance

While AI offers great potential for productivity gains, the gains, if materialized, might not be evenly distributed.[77] Taxation and social transfers can help ensure that AI-induced productivity gains also benefit workers broadly,[78] but premarket policies such as collective bargaining and social dialogue are also important for guiding a fair and inclusive transition towards an AI-powered economy (spotlight 6.3).

To do so, worker inclusion and influence in workplace AI governance is crucial. The generative nature of some AI implies that human oversight, control and contextual understanding matter both to maximize potential and to avoid risks associated with overreliance on AI systems.[79] When human involvement in work is diminished, it can lead to moral disengagement, where individuals become detached from the ethical and behavioural norms that usually guide their actions.[80] When people feel disconnected, their sense of accountability may diminish, increasing the risk of errors and safety issues—especially in highly automated settings.[81] Algorithmic management systems, designed to improve efficiency through monitoring and automation of work allocation, may instead increase errors and disrupt entire workflows if they push workers to engage in multitasking and to oversee simultaneous workflows at ever higher speed (box 6.3).

Similarly, digital surveillance in the workplace—including email monitoring, keystroke tracking and social media scrutiny—can create considerable psychological stress for employees.[82] While these practices aim to enhance productivity and data security, they also contribute to workplace anxiety.[83] Employees can feel a loss of freedom and trust when subjected to excessive surveillance, reducing their motivation and job satisfaction.[84]

Instead, engaging workers in the design and deployment of AI systems can enhance their roles and boost AI's productive impact. Transparent AI interfaces that provide real-time explanations can reduce confusion and cognitive overload, enabling workers to interact with AI more intuitively and effectively.[85] Employers should involve employees in discussions about surveillance policies, provide training on the use of monitoring data and ensure that employees are informed of how their data are used.[86] Workers who feel included in monitoring decisions are more likely to accept them.[87] An opt-in approach to monitoring, where employees have agency over how their data are used, can further reinforce trust and workplace wellbeing.[88]

Furthermore, the allure of AI has created an image of almost completely autonomous systems, nearly free from human intervention beyond the brilliant programmers who developed them.[89] In reality, AI depends heavily on human workers in every step of the supply chain. Lower-value-added activities, such as data labelling and annotation, are often concentrated in low- and middle-income countries, requiring intensive human labour but offering limited rewards. In contrast, higher-value-added tasks, such as AI model design and deployment, are confined largely to high-income countries, demanding specialized knowledge and infrastructure.[90]

The reliance on human labour across the AI supply chain highlights the need to examine who contributes to AI systems, under what conditions and how the value they create is distributed. As AI expands and becomes ever more integrated into our economies, it presents an opportunity for high-quality technology-generated jobs. A complementarity economy recognizes and values workers at every stage of the supply chain,[91] towards ensuring meaningful opportunities, fair compensation and decent working conditions. The future of work in the age of AI should be one of genuine collaboration between humans and machines[92]—not one built on a hidden global workforce facing decent work deficits.

Driving innovation with intent: Aligning socially and privately valuable AI research

Aligning socially desirable with privately profitable AI research and development is a transformative opportunity to advance human development.[93] AI might become more than just another technological innovation able to execute or augment tasks. Like other technological innovations, it can increase the productivity of factors of production, but it differs in that it can also increase the rate of technological innovation.[94] AI's potential to improve the productivity of research and innovation is particularly important in today's world, given evidence that disruptive science and technological innovation was declining through 2010 (figure 6.6).[95] The number of researchers that is required today to keep Moore's law going (the doubling of the number of transistors in an integrated circuit every two years) is 18 times more than in the early 1970s.[96]

But despite AI's potential to accelerate technological progress and scientific discovery,[97] current innovation incentives are geared towards rapid deployment, scale and automation—often at the cost of transparency, fairness and social inclusion.[98] Furthermore, disparities in funding and expertise have resulted in uneven participation in AI research and development.

Thus, driving innovation with intent means harnessing AI for science and technological innovation and steering AI towards human development through incentives, including novel AI benchmarks, and through multistakeholder partnerships.[99] Open source AI can expand access to AI tools and foster broader participation in innovation. While openness also raises critical privacy and security concerns,[100]

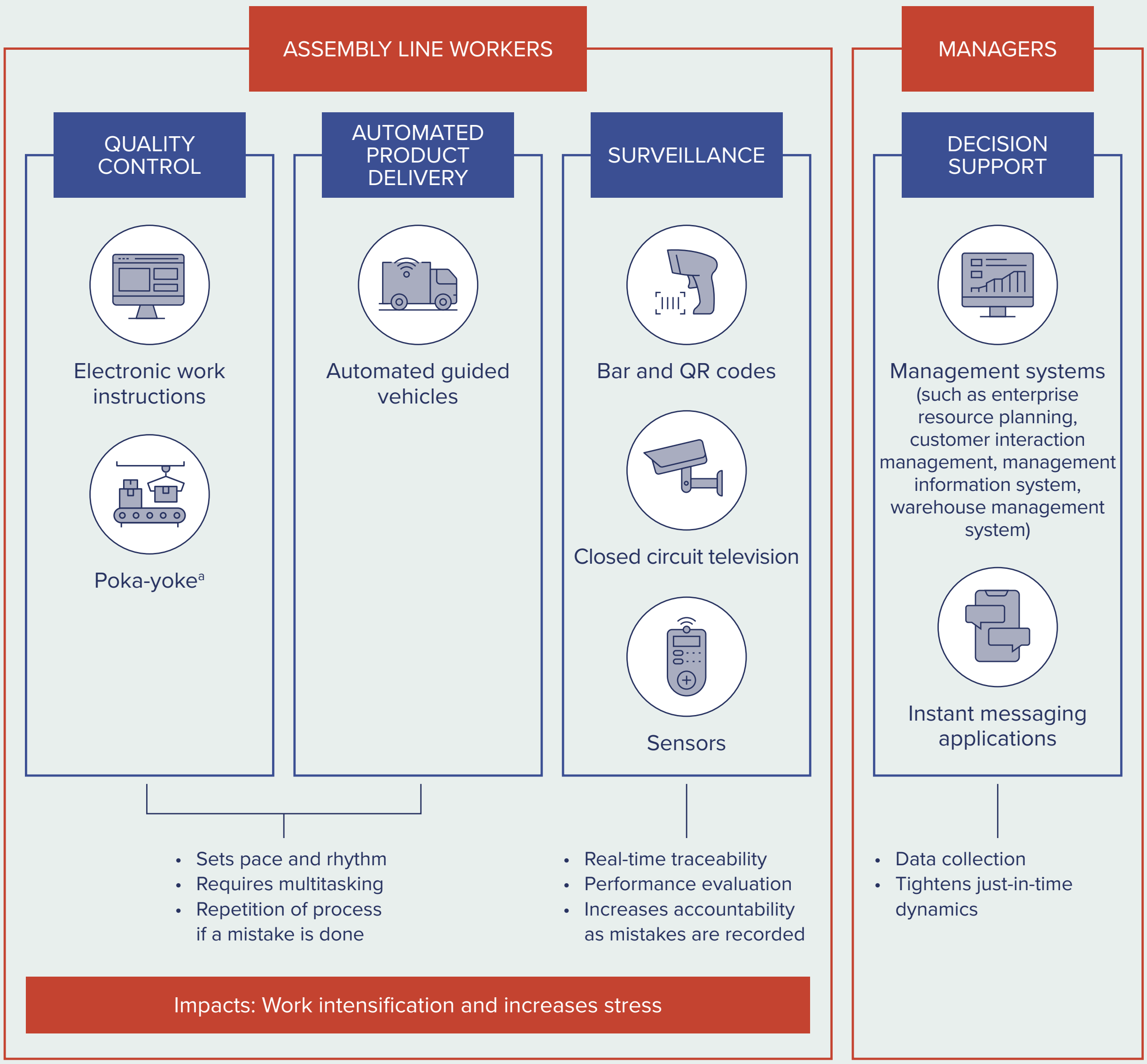
Box 6.3 Who's the boss? The rise of algorithmic management in the automobile manufacturing sector

Uma Rani and Morgan Williams, International Labour Organization

Many of today's algorithmic management tools are rooted in 1980s and 1990s technologies.[1] In automobile manufacturing electronic work instructions and other systems were introduced to prevent errors along the assembly line. Their functionality has advanced considerably, resulting in systems that often layer new capabilities onto older operating systems.[2]

Today the integration of sensors and data management software in the automobile sector has intensified the work pace, monitoring and traceability (box figure 1). Automated systems dictate workflows, often pushing workers to keep up with a relentless machine-driven pace and increasing the demand for workers to maintain speed and meet targets. This is done through both electronic work instructions and automated guided vehicles. In addition, workers and mid-level managers may be required to monitor multiple screens, inputs and outputs simultaneously, often while performing physical tasks on the assembly line.

Box figure 1 Contemporary algorithmic management in automobile manufacturing



a. Pick-to-light and pick-to-voice systems that use light signals and voice instructions respectively to guide workers in executing their manual tasks.
Source: Rani and Williams forthcoming).

(continued)

Box 6.3 Who's the boss? The rise of algorithmic management in the automobile manufacturing sector *(continued)*

The pressure to maintain speed created by automated systems that are designed to reduce errors and the complexity of multitasking that the systems introduce can paradoxically increase the likelihood of mistakes. When errors occur, the system often requires repeating the entire process or segment, further disrupting the workflow and potentially reducing overall productivity. Real-time data tighten just-in-time processes, as any deviation from the prescribed workflow can have immediate repercussions across the entire production line. This technological integration also enables granular, real-time traceability of worker actions, creating a panopticon-like environment (observing workers who do not know whether they are being observed). The possibility of linking errors to individual workers can foster fear and stress, as workers feel constantly scrutinized and apprehensive about making even minor mistakes. The data collected can be used for performance reviews, compensation considerations, promotion opportunities and even job security.

The constant surveillance, pressure to meet algorithmically determined targets and potential for disciplinary action based on automated performance metrics erode the trust between managers and workers. So it is important to shift the balance of power towards workers and take steps to rebuild trust, emphasizing human oversight and worker empowerment. The pace and rhythm of work dictated by these systems must be reassessed and set within more realistic timeframes and parameters that prioritize worker wellbeing and acknowledge the limits of human capacity. Algorithmic systems should be tools that assist workers, not instruments that control and constrain them.

Codetermination and social dialogue are essential for regulating the impact of technology. Meaningful worker participation in the design, implementation and governance of these technologies is paramount—not only consultation but also genuine negotiation and shared decisionmaking over how the systems are used and how performance is measured. Workers, with their intimate understanding of the work process, are best positioned to identify potential pitfalls and unintended consequences of algorithmic management.

Note

1. This box builds on Rani and Morgan (forthcoming). **2.** Krzywdzinski, Gerst and Butollo 2023.

research can be directed to address some of the vulnerabilities of open source technologies by involving a wide variety of organizations with different goals and incentives.[101]

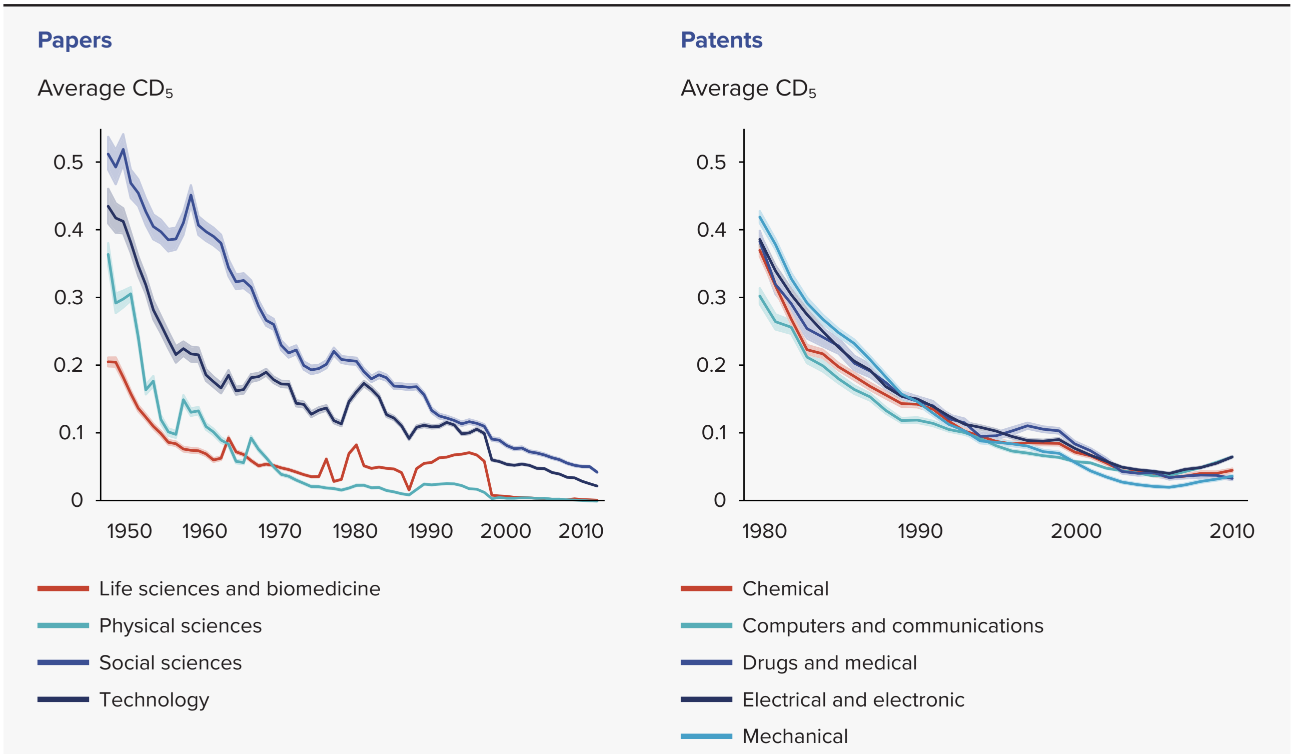
Harnessing AI as the invention of a method of invention to expand human understanding and creativity

AI's potential to accelerate technological innovation and human creativity is illustrated by the improved performance of human Go players. Essentially flat for decades, human performance in the game started to increase after the AI model AlphaGo beat the leading Go master in March 2016 (figure 6.7). Fan Hui, then the European Go champion, was both awed and surprised in describing one of AlphaGo's moves: "It's not a human move. I've never seen a human play this move. So beautiful."[102] The higher quality of human Go players' moves was due to their novelty, not to copying of AlphaGo's moves. AI inspired human creativity by doing something never seen before, augmenting human intelligence.[103]

Though evidence suggests that AI can trigger creativity and innovation across a variety of contexts,[104] the reasons that AI and human collaboration are more likely to do so remain under examination.[105] Deploying AI in research requires consistency with the norms of scientific practice.[106] AI will likely require changes in the way humans interact with it, rather than simply replacing classical programming with AI-powered tools. For example, using AI-summarized results from web searches tends to lead to shallower knowledge and less original advice than a traditional web search.[107] One must look at AI as going beyond simply plug and play, beyond replacing existing research methods with AI.

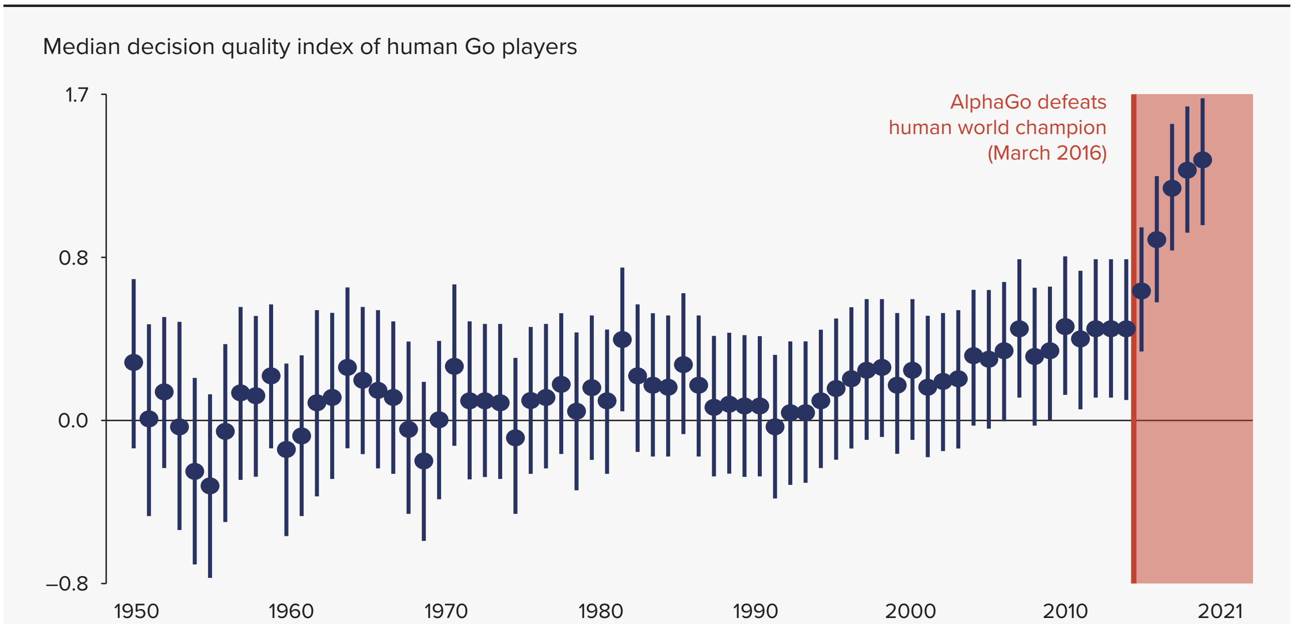
Guidance is emerging on how to make the best use of AI to advance science and the kinds of risks to watch for.[108] Focusing on the key complementarities between humans and AI in the creative process provides a forward-looking perspective.[109] One complementarity is that AI does some things very well that are harder for humans (seeing new things in data), while humans do other things well that AI struggles with (seeing things not in data to generate novel theories).[110] Mixing forecasts from AI models with those from human experts yields better predictions than those of human experts

Figure 6.6 **Disruptive science and technological innovation was on a steady decline through 2010**



Note: CD_5 (calculating disruption) is an index of the extent to which a paper or patent disrupted established scientific or technological knowledge, rendering it obsolete and charting new directions. It measures disruption by the extent to which citations of a disruptive paper or patent also cite its predecessors, with 0 corresponding to consolidation of existing knowledge and 1 corresponding to disruptive. The index is measured five years after the paper was published (hence the subscript 5).
Source: Park, Leahey and Funk 2023.

Figure 6.7 **Artificial intelligence can inspire humans to reach new heights in creativity**



Note: Vertical lines are 95 percent confidence intervals, excluding the potential effect of memorization of AlphaGo moves after 2016.
Source: Shin and others 2023.

or AI alone.[111] And AI combined with remote sensing can help identify tipping points in natural systems—providing essential information for buffering against changes in the natural world.[112]

Scientific discoveries are at times limited by the rate at which existing approaches parse and process data. For example, the search space for new materials is vast, with as many as 10108 organic molecules as possible candidates.[113] The vast majority of these compounds may be of limited, if any, practical value, such that searching the space efficiently is unreasonable for human effort alone. But techniques that use AI to identify candidates are rapidly improving, empowering humans by narrowing the search.[114] In materials science an AI application led to the discovery of 2.2 million new crystals.[115] And in another application AI-assisted researchers discovered 44 percent more materials than the pre-AI trend, increasing patent filings by 39 percent and downstream product innovation by 17 percent.[116] Similar applications of AI to detect data patterns that may not be perceptible by humans can extend to the economic and broader social sciences.[117]

Applications of AI are spreading rapidly across many fields, with published scholarly papers engaging AI increasing from around 2 percent in 2015 to over 8 percent around 2024.[118] In the humanities AI can augment the availability of historical economic data.[119] In archaeology AI has enabled archaeologists to double the number of identified figurative geoglyphs in Nazca, Peru, insights that led researchers to a new hypothesis.[120] Applications of AI in economics are accelerating[121] and spreading to other social sciences, including political science.[122] Applications also span a range of scientific and technological fields, including biology,[123] chemistry,[124] conservation science,[125] drug discovery,[126] geology,[127] materials science,[128] mathematics,[129] neuroscience,[130] physics[131] and psychology.[132]

Augmenting AI with scientific models can combine understanding that comes from science with the AI capabilities to extract patterns from data.[133] Applications include combining physics-based models to predict weather and climate, with AI trained on past weather data to improve forecasting.[134] There is also potential to leverage the complementarity between humans and AI to enhance innovation at larger societal scales, beyond specific labs or scientific fields, by enhancing collective intelligence.[135] Fully leveraging the potential of complementarity between AI and human creativity requires making people more aware of the risks.[136] It also requires purposefully building machines meant to learn and think with people rather than just focusing on the capabilities of machines that surpass people.[137]

The pursuit of human and AI collaboration to advance arts and science needs to consider novel risks and challenges that are under close scrutiny and add uncertainty to whether AI's potential for accelerating innovation can be fully realized.[138] Broader systemic implications of AI use to boost scientific productivity include the potential tradeoff between affecting individual creative productivity with AI and making creative output less diverse, potentially leading to less collective diversity of novel content.[139] The implications for job satisfaction and deriving meaning from work when interacting with AI are still not well understood.[140] The synthetic data produced by generative AI create new ethical challenges for scientists,[141] including how to fulfil norms of scientific conduct such as accountability, transparency, replicability and human responsibility.[142] And adequately compensating creators of much of the content to train AI raises new questions related to intellectual protection law and liability when things go wrong.[143]

> “AI's contributions to science will likely be greatest when it augments humans doing the science

So, despite AI's potential its applications in science and research can produce flawed, overly optimistic or hard to reproduce results.[144] More fundamentally, the goal is not to produce more science but to understand more about the world and about ourselves, and there is a risk that the proliferation of AI in science will yield more results but less understanding.[145] From a human development perspective the value of science ultimately comes not from the nominal rate of discoveries but from the rate at which those discoveries are important to people. It is also crucial to see science and creative processes more broadly as inherently human endeavours—where spontaneity and serendipity from interactions between humans, as well as very human mistakes that no machine would make, can engender creativity.[146] AI's contributions to science will likely be greatest when it augments humans doing the science.

Aligning AI research towards advancing human development

Ensuring that AI advances human development depends in part on aligning AI innovation incentives in different ways. That includes, for instance, avoiding creating innovation traps,[147] which could undermine AI paths that advance human development.[148] This could be achieved if AI research and development adopt a broader perspective seeking to align AI advancements with societal goals, pluralism and inclusion rather than being narrowly driven by contested or speculative pursuits.[149]

"One aspect of the human development–aligned AI path relates to safety, an area that has yet to receive investment and research attention commensurate with its potential economic and social impact

To foster AI innovation that enhances human development, AI benchmarks, which have become fundamental tools for evaluating the performance, capabilities and safety of AI models, could also be expanded. While important, current metrics tell us very little about how much AI is augmenting human development. To align AI more closely with human development, new benchmarks should be researched and deployed, assessing how AI contributes to human wellbeing, opportunity and agency (chapter 4).[150]

Tax strategies can incentivize greater financial commitments from major technology companies and public entities and steer research and development towards AI systems that advance human capabilities, while discouraging investment that promotes automation-driven labour displacement. Tools such as public–private partnerships, public procurement policies, regulatory sandboxes, impact-based funding and outcome-driven investment mechanisms, along with novel benchmarks, can help shift the balance.[151] Together, these measures could fund and rebalance AI research and development towards human development–enhancing technologies.

Another aspect of the human development–aligned AI path relates to safety, an area that has yet to receive investment and research attention commensurate with its potential economic and social impact,[152] given that AI safety accounts for only about 2 percent of overall AI research.[153] While fields such as computer vision dominate due to their extensive commercial applications and robotics continues to thrive in industrial contexts, AI safety remains a marginal focus in most AI applications and across regions.[154] Even in research-intensive regions such as East Asia and the Pacific and OECD members, AI safety is underrepresented. For example, although China and the United States lead global AI research, their priorities diverge—with Chinese efforts centring on robotics and computer vision and US research slightly favouring natural language processing, alongside a modest lead in AI safety.[155]

Another promising area of research is small language models, which, unlike large language models, offer advantages in data security and privacy because they are designed for specific use cases, providing more targeted, cost-effective and secure solutions.[156] This makes them particularly well-suited for developing country settings, where resource constraints are a critical consideration. Deploying small language models without internet connectivity is feasible through on-device implementation. This approach increases data privacy, reduces latency and ensures continuous operation in areas with unreliable internet access. Take InkubaLM, a small language model designed to make AI tools more accessible for African languages. It performs as well as larger models while being more efficient, using two specialized datasets to enhance tasks such as translation and sentiment analysis. By advancing research on smaller models, researchers can create fairer, more sustainable AI options for underserved and lower-resourced communities.[157]

The disparity in AI resources, expertise and infrastructure between high-income and low- to middle-income countries—directly affects who benefits from AI and who is left behind.[158] High-income countries possess substantial investment capacity, technological infrastructure, data and AI talent, enabling them to lead in AI innovation and AI safety (chapter 5). In contrast, many low- and middle-income countries struggle with insufficient funding, weak digital infrastructure and a shortage of skilled professionals, limiting their participation in AI development.[159] This divide not only restricts access to AI benefits but also reinforces global inequalities in advancing AI for human development.

Strengthening global collaboration through partnerships[160] would promote a more balanced distribution of AI benefits, ensuring that regions at all income levels can contribute to and benefit from AI-driven progress.[161] Low HDI countries experienced the fastest growth in collaborative AI research outputs between 2014 and 2023. This is a positive sign, but it is due mainly to a low baseline—in fact, the gaps widen substantially as HDI increases. Medium HDI countries also made considerable progress, while high and very high HDI countries exhibited slower but solid growth. In absolute terms there is divergence: the distance between low HDI countries and very high HDI countries is now larger than a decade ago.[162]

Partnerships would need to be structured to ensure that local priorities are not overshadowed by the interests of higher HDI countries.[163] AI safety frameworks must incorporate diverse perspectives, accounting for regional ethics, governance structures and societal norms.[164] This inclusivity is essential to strengthening AI safety outcomes, ensuring that AI tools are both contextually relevant and globally adaptable. Partnerships in AI not only bring together diverse areas of expertise but could also drive substantial investment in digital infrastructure, research and talent development. By aligning the interests of government agencies, academic institutions, industry leaders and the broader public, these collaborations would help ensure that future AI progress advances human development (box 6.4).

Box 6.4 Bridging bytes and governments: Artificial intelligence ecosystems through partnerships

Several countries are pioneering new models for inclusive artificial intelligence (AI) ecosystems and partnerships. For example, the Republic of Korea is a global leader in AI research and development, with a mix of public and private investment in frontier technologies leading to more than 1,500 AI patent filings in the first 10 months of 2024.[1] The National AI Computing Center, backed by joint public–private investment,[2] aims to enhance Korea's AI research infrastructure and secure high-performance computing resources (graphics processing units). The initiative is spearheaded by the Ministry of Science and ICT in collaboration with the Ministry of Economy and Finance, the Ministry of Trade, Industry and Energy and the Financial Services Commission.[3] Complementing this, Korea is launching the National AI Research Hub in 2025 to foster collaboration between government and industry and to accelerate AI development nationwide.[4]

Similarly, AI Singapore brings together Singapore-based research institutions, AI startups, companies and the public sector to develop national AI capabilities and foster a trusted AI ecosystem that addresses global challenges such as health and climate change.[5] And AI Sweden operates as a nonprofit partner network of more than 150 organizations spanning diverse sectors and disciplines—from AI experts, data scientists, research engineers, linguists and mathematicians to policy specialists, lawyers, journalists and changemakers—working together to drive sustainable and inclusive AI progress across, for example, healthcare, energy systems and local municipalities in Sweden.[6]

Another example is Current AI, which highlights the transformative potential of public–private partnerships by developing AI solutions that serve the public interest through global collaboration and local implementation. The initiative focuses on building an open AI ecosystem by unlocking valuable datasets, promoting open standards and tools to increase accessibility and ensuring transparency and trust through public interest auditing and oversight. Backed by major technology companies—including Google—and the French government, Current AI aims to deliver AI systems that genuinely serve the public good.[7]

The private sector is also advancing multistakeholder alliances. For example, the Partnership on AI is a global nonprofit organization[8] whose founding members were Amazon, Facebook, DeepMind, Google, IBM and Microsoft. It unites more than 100 partner organizations from industry, academia and civil society to address the societal implications of artificial intelligence. By fostering collaboration among diverse stakeholders, the organization develops best practices, conducts research and promotes the responsible development and use of AI technologies. Through initiatives such as creating frameworks for safe AI deployment and investigating challenges to diversity in AI, it aims to ensure that AI advancements are ethical and transparent.

These examples show that partnerships offer a structured and scalable approach to ensuring AI as a safe and equitable technology aligned with human development priorities.

Notes

1. Buntz 2024. **2.** Dae-Hyun 2024. **3.** Kim Eun-jin 2025. **4.** Republic of Korea Ministry of Science and ICT 2024. **5.** Smart Nation and Digital Government Office n.d. **6.** AI Sweden n.d. AI Sweden is funded by Sweden's innovation agency Vinnova, the Swedish Agency for Economic and Regional Growth, the European Regional Development Fund, and contributions from its network of partners. **7.** Current AI n.d. **8.** PAI 2024.

Investing in capabilities that count: Can AI enhance education and health outcomes?

AI offers new possibilities to advance human development by enhancing achievements in education and health, but substantial challenges are inherent in its deployment. Underresourced institutions are more likely to adopt questionable AI solutions—a tendency closely tied to technosolutionism (chapter 4).[165] Often the focus is on deploying technology (such as one laptop per child) or cultivating specific technology-based skills (coding) without sufficient attention to the broader goal of enhancing human development. The context—alongside the human and social factors essential for successful institutional transformations—tends to be overlooked. And context varies considerably. The initial conditions for AI deployment are highly unequal—and are becoming increasingly so in the areas closely linked to human agency and empowerment. If this reality is not carefully considered, AI's introduction may prove ineffective or even counterproductive..

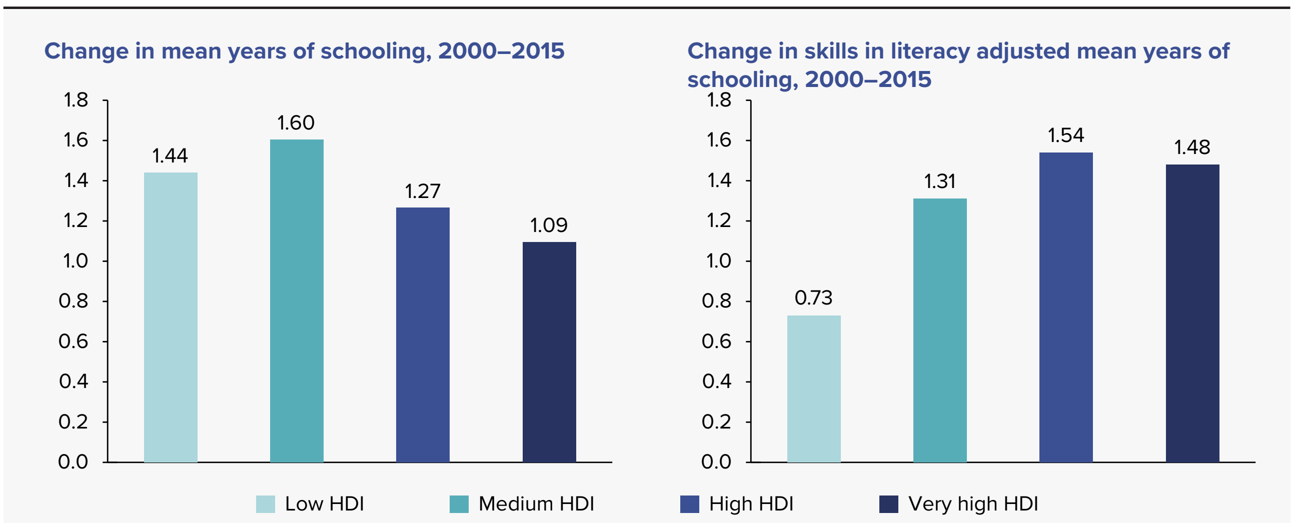
A baseline of high inequality in enhanced capabilities in education and health

The notable progress in education and health outcomes over the past few decades has focused on basic capabilities and quantity-based metrics. For example, expected years of schooling are at their highest on record, and the global percentage of children out of primary school is now in the single digits.[166] In health, life expectancy at birth has increased by 8.4 years globally since 1990.[167]

But gaps persist and even widen when it comes to enhanced capabilities, as highlighted in the 2019 Human Development Report. In education there are enormous gaps in students' functional competencies.[168] Globally, only around 40 percent of children achieve basic skills in math and science.[169] The proportion ranges from about 4 percent in low HDI countries to 67 percent in very high HDI countries.[170] Despite a substantial reduction in disparities in the earliest stages of education, serious inequalities persist and grow in later stages and in learning outcomes (figure 6.8).

In health there are sizeable differences across the globe. The gap in life expectancy at birth is 30 years: between 55 years in Nigeria and 85 years in Japan.[171] Around half the world's population lacks complete coverage of essential health services.[172] And while gaps in mortality linked to communicable diseases have narrowed—leading to lower infant mortality—mortality disparities have increased at older ages. Lower-income countries are progressing much more slowly in developing health systems with adequate coverage, resources and equity.[173]

Figure 6.8 Education—convergence in basic capabilities, divergence in enhanced capabilities



Note: Each bar measures the mean value for countries within each Human Development Index (HDI) group.
Source: Human Development Report Office based on Lutz and others (2021).

Enhancing education capabilities to seize AI's potential

Seizing AI's potential starts with shifting the focus in education from quantity to quality.[174] AI may change cognition and the skills important to strive for.[175] High-quality learning requires the ability to understand the world, critically assess large amounts of information, define objectives and apply knowledge in an ever changing and complex environment. Three core areas need attention as AI diffuses: critical thinking, creative thinking and relational thinking.[176]

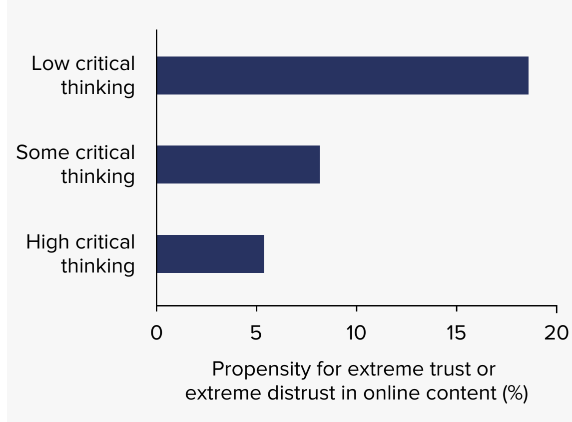
Critical thinking is vital for evaluating large amounts of information and making decisions that align with one's values and circumstances.[177] For instance, extreme trust or distrust in online content signals an inability to properly assess and use internet resources. Recent data from the Programme for International Student Assessment show that 15-year-old students with low critical thinking are more than three times as likely as those with high critical thinking to indiscriminately accept or reject information from online sources (figure 6.9).

Creative thinking—the cognitive process that generates, assesses and improves valuable and original ideas[178]—is essential for adapting to evolving circumstances and setting new goals and priorities. Relational thinking is crucial for making decisions in a context of interdependence—whether with the people around us (empathy, compassion), our societies (responsibility, citizenship) or our planet (recognition of our embeddedness in nature).[179]

Deploying AI to strengthen interventions that improve learning outcomes

To enhance human learning, AI will have to be implemented to support learning strategies that are known to be effective[180] rather than being deployed in education for its own sake. Personalized and adaptive learning interventions are such strategies. For example, adaptive learning technologies improve math achievement,[181] and the benefits of interventions such as structured pedagogy and "teaching at the right level"—as opposed to teaching in accordance with age cohort—are 65 times their cost when applied at scale in low- and middle-income countries.[182]

Figure 6.9 Critical thinking mitigates students' propensity towards extreme trust or distrust of online content



Note: Based on data for 52 countries. Extreme trust refers to respondents who answered "I strongly agree" with the statement "I trust what I read online," and extreme distrust refers to respondents who answered "I strongly disagree" with the statement. Critical thinking is proxied using scoring groups (on a scale of 1–6) for mathematics, reading and science, based on the qualitative descriptions of achievement at each level. High critical thinking: level 4 or above in all three subjects. Some critical thinking: level 4 or above in at least one subject Low critical thinking: below level 4 in all subjects.
Source: Human Development Report Office calculations using data from the 2022 Programme for International Student Assessment.

In many resource-constrained settings even more traditional technologies such as mobile phones can enhance learning cost-effectively and equitably, as demonstrated by Kenya's SMS-based M-Shule platform (chapter 3)[183] and Botswana's SMS and phone call intervention.[184] Randomized controlled trials in India, Kenya, Nepal, the Philippines and Uganda demonstrate that phone call tutorials can scale effectively, offering targeted instruction that caters to students' learning needs.[185] Another example is intelligent tutoring systems, which can improve personalized learning, streamline classroom and administrative processes and promote collaborative, self-directed education[186] while reducing costs and administrative burdens.[187] Still, feedback options and expert supervision remain crucial.[188]

AI has the potential to greatly enhance the education benefits made possible by these earlier technologies. In Sierra Leone, where high internet costs result in low connectivity, AI-driven solutions offer a cost-effective alternative that is 87 percent cheaper than a web search.[189] For AI-powered tutoring targeted instruction and personalization have proven effective in improving learning outcomes in Ghana[190] and

Nigeria.[191] Instruments need to be customized: targeting instruction to students' learning levels rather than simply to their grade, significantly improves education outcomes. For example, a targeted pedagogical intervention in Türkiye, achieved through teacher training, boosted children's curiosity, knowledge retention and learning outcomes.[192]

AI in education can also address challenges such as cyberbullying, where general empathy training, modifying beliefs supportive of aggression and more specific guidelines for internet behaviour are required.[193] It can support learners with disabilities[194] and create opportunities for women[195] by helping them upskill, reskill and increase participation in underrepresented science, technology, engineering and math fields.[196]

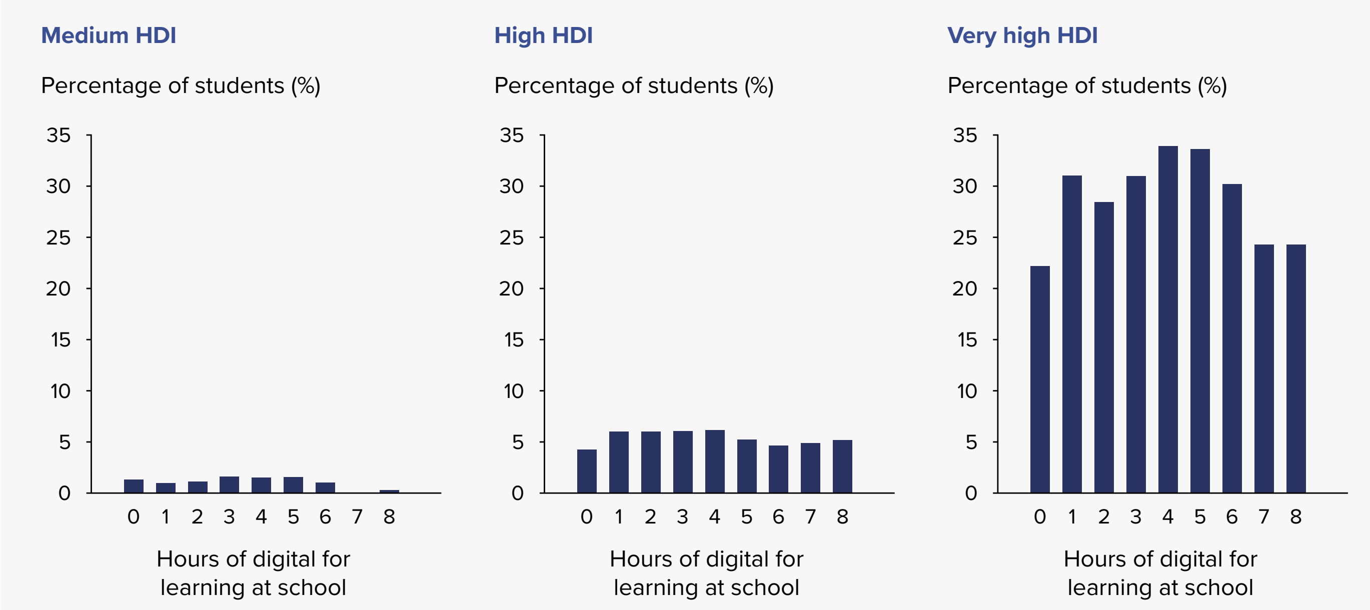
AI deployment can be informed by how technology can support parental engagement.[197] Telementoring and homeschooling in Bangladesh during the Covid-19 pandemic boosted students' test scores by 35 percent, increased mothers' involvement by 26 percent, prevented learning loss and had lasting benefits, especially for lower-performing students.[198] Parenting strategies—along with children's education, strategic physical activity and counselling—have proven effective in preventing or reducing internet addiction. Interventions that shift children's focus from online activities to real-world activities have shown promise in reducing internet engagement, preventing addictive behaviours.[199]

AI on its own will not fix education challenges

Technology-driven interventions do not always yield positive results. Interventions that only add an additional input (such as a computer) to the education process are consistently ineffective. In Costa Rica and Peru there were no notable impacts on academic achievement or cognitive skills from providing laptops to children at home.[200] Even access to fundamental services such as electricity might not have a noticeable effect if not accompanied by complementary measures.[201]

Despite the promise of AI in education, use of digital devices has not improved student outcomes across the board,[202] sparking dissatisfaction and, in some cases, protests among students and teacher unions.[203] While digital resources can yield positive effects for learning, the benefits diminish with excessive use (figure 6.10). Data from the 2022 Programme for International

Figure 6.10 The benefits of digital resources for learning critical thinking diminish with excessive use



HDI is Human Development Index.
Note: Pooled observations with equal weights across countries. Critical thinking is proxied using scoring groups (on a scale of 1–6) for mathematics, reading and science, based on the qualitative descriptions of achievement at each level. For each group the bars show the percentage of students who reached level 4 or above in at least one subject.
Source: Human Development Report Office calculations using data from the 2022 Programme for International Student Assessment.

Student Assessment show declining reading and math scores in OECD countries, with excessive mobile phone use for leisure correlated with poorer outcomes.[204]

Gains from using digital technologies in education at school are greater in higher HDI countries. In medium HDI countries increasing digital resources in schools tends to be less effective on average. One study shows Indonesia, at the lower end of high HDI countries, could benefit from integrating large language models into education to reduce educators' workload and support interactive, personalized learning, though issues related to ethics, data privacy, reliability, accuracy and cost persist.[205] AI in education risks exacerbating inequities due to unequal access to digital connectivity and technology.[206] Without proper governance and targeted policies, issues related to accessibility, transparency and fairness in AI-based systems may lead to discrimination and exclusion,[207] further entrenching existing disparities and raising concerns about environmental impacts.[208]

> "Successfully integrating AI into education requires effective classroom practices, teacher collaboration and attention to local education goals, with human interaction playing a crucial role in shaping student perceptions and learning outcomes

Successfully integrating AI into education thus requires effective classroom practices,[209] teacher collaboration and attention to local education goals, with human interaction playing a crucial role in shaping learning outcomes.[210] AI's potential suggests that a combination of institutional and human capabilities is needed to improve education outcomes. Even when technologies such as video lectures are used, an instructor's online presence increases student motivation and engagement.[211] Blended learning, combining online and face-to-face instruction, also shows benefits.[212] Teachers' characteristics, self-efficacy and alignment with student needs are crucial in technology integration, as are supportive school environments and infrastructure.[213]

Given challenges with plagiarism, bias and overreliance, careful attention must be paid to the design and implementation of generative AI in education,[214] while maintaining opportunities to enhance learning through content generation, personalized tutoring and instructional support.[215] Digital literacy programmes can be incorporated into school curricula, with self-monitoring tools and behavioural interventions such as video modelling and group contingencies.[216] Schools can also raise awareness about the addictive nature of digital experiences and promote responsible online behaviour.[217]

Overreliance on generative AI can hinder student motivation and intellectual engagement,[218] while weak pedagogical designs can minimally improve learning outcomes (chapter 3).[219] Metareviews of intelligent tutoring systems show modest learning gains,[220] with effectiveness influenced by students' prior knowledge.[221] Although AI can create personalized learning experiences,[222] both humans and AI need to adapt to ensure successful integration of technology in education.[223] In teaching maintaining social cues such as gestures, facial expressions and eye gaze remains crucial.[224] Adopting educational technologies without considering the context brings challenges such as high costs, teacher shortages[225] and concerns over AI's inability to replicate the social, emotional and cognitive roles of educators[226] and overreliance on technology.[227]

AI can enhance health outcomes if health inequalities are redressed

AI offers multiple opportunities to personalize, expand access to and increase the quality of healthcare by predicting,[228] diagnosing[229] and managing diseases[230] while supporting clinical decisionmaking and medical workflows.[231] It can improve patient care, quality assurance and overall healthcare operations, leading to better health outcomes.[232]

Use cases of AI in healthcare already abound.[233] AI enhances disease detection, classification and monitoring through machine learning models in health systems.[234] With noncommunicable diseases accounting for the majority of global mortality and morbidity, AI-driven tools can help address the rising burden of chronic conditions such as heart disease, diabetes and respiratory illnesses.[235] AI can generate high-quality data and support systematic reviews to better understand the links among diet, nutrition and chronic diseases.[236] By providing personalized medical information, lifestyle guidance and treatment details,[237] AI-driven tools can empower people to manage noncommunicable diseases. Mobile apps, reminder systems and AI chatbots enhance communication with physicians and may improve treatment adherence.[238]

The promise of AI-enhanced healthcare in low-income settings with limited access to specialized expertise is especially important.[239] For example, AI can help community health workers screen for severe diseases, such as breast cancer,[240] or detect leukaemia with just 10 laboratory parameters,[241] enabling early detection in low-resource and emergency settings.[242] In countries with high neonatal mortality rates, such as India, Nigeria and Pakistan, AI can assist mothers with early screening and diagnosis of noncommunicable and nutrition-related diseases.[243] Innovative solutions, such as voice bots in Bangladesh, show how AI can support women's healthcare needs.[244] Further, predictive analytics enable real-time surveillance of infectious outbreaks using genomic, environmental and patient data.[245]

No AI in health without trust, less trust without redressing health inequities.

Much of AI's potential is hampered because concerns about bias, trust and privacy hinder AI adoption in health.[246] Limited health infrastructure, skewed datasets and algorithmic flaws can deepen healthcare disparities, while lack of transparency and governance gaps erode trust. For example, the integration of large language models into Philippine ophthalmology shows great potential but is hindered by challenges such as limited local data, technical expertise, funding and regulatory oversight.[247]

Even before AI, telemedicine and mobile health expanded access to healthcare, but adoption was often hindered by technological gaps and resource limitations.[248] Now, AI-driven telemedicine could improve care for elderly populations in remote areas, though unequal access to healthcare data can worsen disparities, even in high-income countries.[249] Thus, the digital divide and healthcare workforce shortages reinforce healthcare inequities,[250] particularly for low-income populations, who are often excluded from data collection and receive lower-quality care.[251] Weak health infrastructure further limits diverse AI development.[252] To close these gaps, ensuring that AI-driven healthcare tools are accessible, affordable and effectively integrated into diverse settings can help reduce rather than deepen disparities.[253]

Gender inequities in healthcare and AI development further reinforce disparities. Despite making up 67 percent of the global health workforce,[254] women hold only 31 percent of global health leadership roles,[255] limiting their influence on AI-driven healthcare. The lack of gender diversity in AI development teams exacerbates this issue, resulting in lower-quality AI products that reinforce stereotypes and discrimination.[256] In addition, gender biases in patient care and limited access to digital health tools disproportionately affect women, particularly those with less education and income.[257] Addressing these disparities requires promoting women's leadership in AI, expanding education in science, technology, engineering and math, eliminating hiring biases and fostering inclusive workplace practices.[258]

> "Many people lack the skills to use AI tools, even ones that are affordable. Mobile health apps, wearables and telemedicine are often out of reach for historically excluded communities

Many people lack the skills to use AI tools, even ones that are affordable. Mobile health apps, wearables and telemedicine are often out of reach for historically excluded communities. Limited digital literacy and poor access to devices or the internet remain, even in high-income countries.[259] Disparities are also linked to AI healthcare research is being concentrated in a few high-income countries.[260] Research output is also uneven: in Africa, Egypt, Morocco and South Africa lead in cardiovascular, diabetes and cancer research, while Egypt, Ghana, Nigeria and South Africa focus on malaria and tuberculosis.[261] Even in high-income countries, access to healthcare data varies widely. As data capacity increases, the gap in countries' ability to make informed health decisions is expected to grow.[262]AI in healthcare requires supportive policies, executive backing, clinical demand and user consensus.[263] Strengthening social protection systems and involving the community in design and implementation can ensure more equitable outcomes.[264]

AI deployment in health requires building trust and ensuring both accuracy and fairness

As AI's clinical significance grows,[265] better integration into clinical practice and workforce development is essential. One randomized controlled trial found that while large language models outperformed physicians in diagnostics, they offered no significant benefit as a diagnostic aid.[266] Similarly, using large language model technology to draft responses to electronic health record messages can reduce messaging burdens on healthcare teams but will remain a supportive aid rather than a comprehensive solution.[267] AI use was also found to be associated with higher risk of radiologist burnout, particularly among those with high workload or lower AI acceptance.[268]

AI in healthcare relies on large datasets and complex algorithms, which can introduce biases and inaccuracies that undermine its effectiveness, particularly for disadvantaged populations.[269] Inadequate clinical validation and weak evaluation frameworks hinder AI's safe and effective use in patient care.[270] For example, AI's potential in brain tumour or melanoma diagnosis depends on data quality, but the underrepresentation of certain populations[271] can reduce its accuracy.[272] Addressing healthcare inequities requires unbiased data and overcoming biases in clinical practices and AI use.[273] Technologies such as pulse oximeters, which overestimate oxygen levels in nonwhite patients, can perpetuate disparities.[274]

"Ensuring transparency in AI-driven decisions through rigorous evaluation of clinical benefits and compliance with methodological standards can prevent biases in clinical workflows

A multistage approach focusing on fairness, transparency and inclusivity can address biases in AI-driven healthcare. For example, only 8 of 27 countries actively use AI for data mining in healthcare, exposing regional biases.[275] Inclusive data sharing, participant-centred development and code transparency could mitigate this.[276] Ensuring transparency in AI-driven decisions through rigorous evaluation of clinical benefits and compliance with methodological standards can prevent biases in clinical workflows.[277]

At various stages specific interventions can address systemic biases during data collection, handle missing data during preparation and reduce model selection bias during development.[278] Algorithmic audits,[279] federated learning, disentanglement techniques and explainable AI would further enhance fairness and accountability.[280]

Addressing individual and systemic concerns builds trust in the use of technology in healthcare. Ensuring compliance with ethical standards, robust data management and continuous monitoring of AI systems fosters confidence. The competence of digital management, as demonstrated, for example, by Mexico's local governments, also influences AI perceptions.[281]

Healthcare organizations must ensure the safe, transparent integration of AI technologies. Collaboration to cocreate AI solutions that meet real-world needs, align with social values and avoid bias fosters public trust. Institutions should prioritize testing, validation, training and continuous monitoring of AI applications in clinical settings.[282] They also have a responsibility to educate the public on AI's strengths and limitations while ensuring accessibility and affordability. Clear explanations of AI's decisionmaking processes can enhance confidence.[283] Transparency through patient notification is crucial for maintaining the trustworthiness of health systems.[284] The credibility of AI professionals also influences public trust,[285] highlighting the need for third-party accreditation, regulatory guidance and AI-specific training for healthcare workers.[286]

At the individual level perceived utility and ease of use of AI and digital tools in healthcare can foster trust.[287] Patient attitudes towards AI are influenced by cultural, age and education factors, affecting adoption and engagement.[288] For example, while African American and Latin American women in general embrace digital health for perinatal mental health,[289] some demographics, such as older women in Chile, prefer in-person care for certain procedures.[290] In this sense AI systems in healthcare should be personalized and patient centred, considering accessibility, family involvement and reminders. Trust between healthcare providers and patients, built on communication and competence, remains essential.[291] AI should enhance, not replace, human interactions, improving access, quality and adherence while addressing power dynamics and patient-provider relationships.

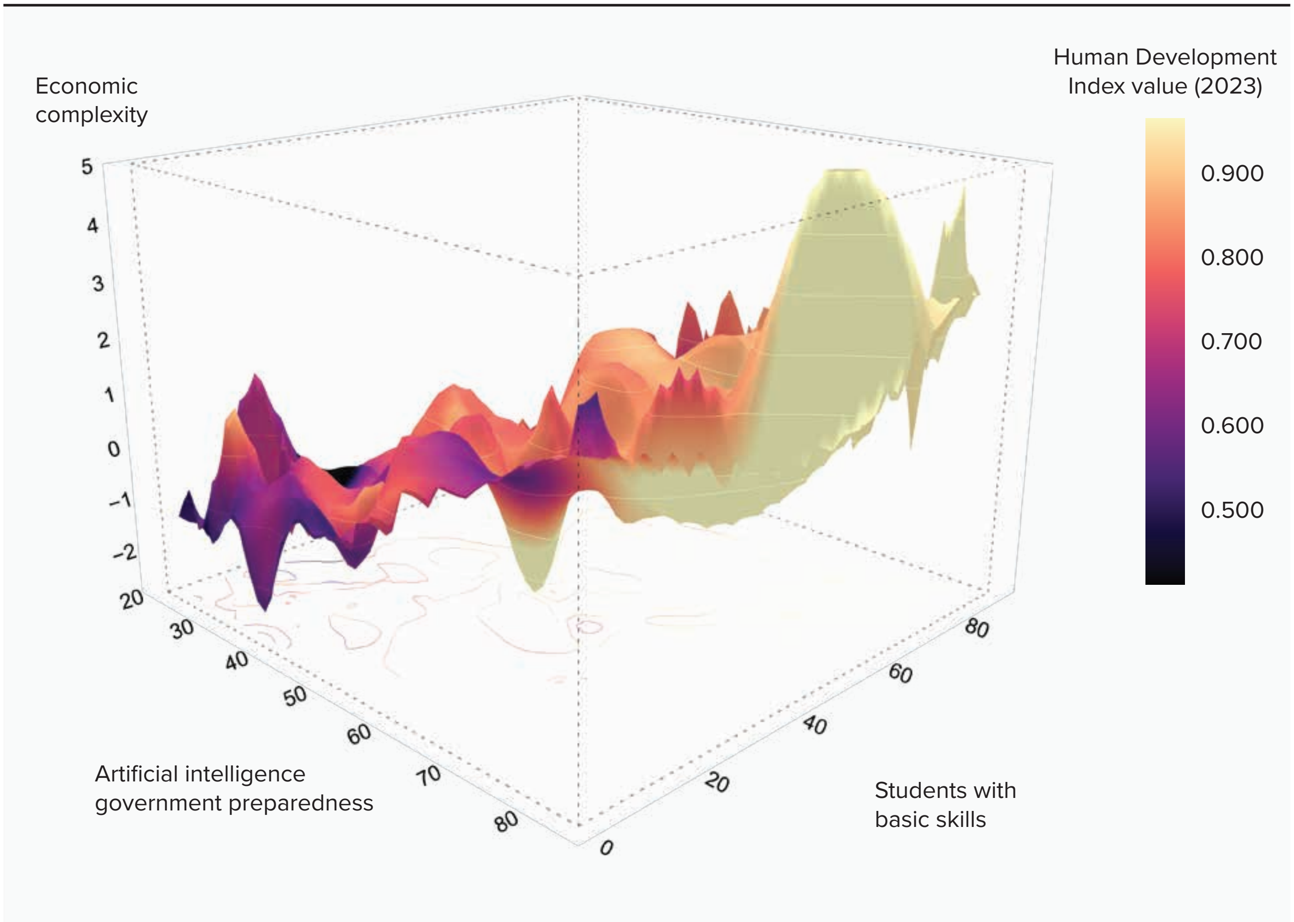
The road ahead: AI's promise to advance human development

As seen throughout this Report, AI holds considerable promise for enhancing human development. Micro- and macro-level evidence points to the potential of AI-driving improvements in individual and aggregate learning outcomes, in public health and personalized medicine and in increasing workers' productivity. Yet without proper attention to context, today's development gaps can be substantial barriers. Where institutions are underresourced, technical fixes are unlikely to yield positive results and may, in some cases, lead to unintended or even harmful consequences.[292]

Development is path dependent. Countries upgrade and diversify their productive structures by building on what exists at each time.[293]

The effectiveness of AI-supported transformation depends heavily on a country's human development, economic and institutional context (figure 6.11). Many countries face compounded challenges. In low HDI countries less than 1 student in 20 has the basic skills to critically engage with new technologies, limiting AI's potential to enhance learning and eventually stifling possibilities for leveraging AI in work. Institutional capacity to integrate AI into public service delivery is also limited in many of these countries, as reflected in low scores on the Government AI Index.[294] At the same time, the economic structures in many of these countries may limit the local economy's potential to absorb productivity spillovers from AI. The economic complexity of many low and medium HDI countries is limited,[295] reflecting a relative lack of diversity of the economy and fewer and weaker links to high-value-added activities. In many

Figure 6.11 Mind the context—initial conditions can compound development challenges



Source: Human Development Report Office based on data on economic complexity (defined as diversity and complexity of a country's export basket) from Harvard Growth Lab (2025), data on the Government AI Index from Oxford Insights (2024) and data on the share of students with basic skills in mathematics and science from Gust, Hanushek and Woessmann (2024a).

of these countries, exports are concentrated in a few commodities[296]—often those with low labour intensity, such as mining and certain types of agriculture—or in activities such as call centres, which are difficult to upgrade. Addressing these gaps is key to moving towards AI-augmented human development. Action in all three areas –a complementarity economy, innovation with intent and capabilities that count, would help.

AI implementation should be properly nested in the local reality. It is important, particularly in low- and middle-income countries, to avoid "vanity" AI projects that have few links to the prevailing patterns of specialization and expertise in a country. This does not mean giving up from the supply side of AI but rather seizing the opportunities of the wide availability and customizability of generative AI while building native AI to the extent of each country's capabilities that seizes on the country's distinctive economic and cultural characteristics—not developing AI for AI's sake.

"Realizing the potential of AI for human development demands policy action that is grounded in the human development realities of each country and centred around the three areas of action: pursuing a complementary economy, driving innovation with intent and Investing in capabilities that count

From there countries can leverage AI to deepen their competitiveness and diversify their economies. AI has spillovers across different areas, and AI investment in one sector can spill over to other sectors of the economy. For instance, in Nigeria, which like many other resource-rich countries faces perennial challenges with diversification, strong AI investment in money, personal finance and business management services could offer pathways towards diversification.[297] Leveraging AI for economic diversification may be particularly important in lower-income economies,[298] as traditional export- and manufacturing-led growth strategies become less attainable.[299]

Realizing the potential of AI for human development requires us to move beyond unhelpful fatalistic or overly optimistic narratives. It demands policy action that is grounded in the human development realities of each country and centred around the three areas of action proposed in this chapter:

Pursuing a complementarity economy implies strengthening the networks that facilitate productive interaction between people and AI. This begins by empowering workers with augmentation opportunities. Countries have several policy levers at hand. First, advance a broad macro-fiscal package that shapes incentives towards investment in labour-enhancing AI and addresses existing development gaps. Universal and meaningful connectivity as a foundational enabler for AI-driven progress is key (spotlight 6.2). Second, include workers in AI gains and governance through social dialogue, ensuring that AI-driven structural transformations deliver decent jobs. Third, strengthen social protection systems and active labour market policies, including through private sector collaborations, that support those whose jobs may be displaced, link them to new productive opportunities and increase the supply of skilled workers.

In innovation with intent, harness the potential of AI to be the invention of a method of invention, giving new wings to humans' perennial aspirations to understand and create. It also means embedding new directions into AI research and development—empowering users through creative engagement, expanding AI safety, augmenting human capabilities through small language models and cautiously developing open source AI—can anchor human agency in the research and development process. This ensures that AI development is recalibrated to drive positive human development outcomes. Additionally, supplementing technical benchmarks with new standards that assess AI's contribution to human development is essential. Establishing a multistakeholder coalition to design and promote these benchmarks would ensure that AI innovations are measured not just by technical standards but by their capacity to advance human development.

When it comes to *capabilities that count*, seize AI's opportunities to personalize education and medicine, expand access and adapt technology-enhanced service delivery to different local realities across groups and development contexts. For health, AI can complement scarce healthcare expertise, especially in resource-constrained settings. Avoid deploying AI for AI's sake and instead use it to enhance and scale up interventions in education and health that are known to work. Ultimately, realizing AI's potential to advance human development hinges on investment in people, not in algorithms alone. For example, moving away from a focus on education quantity to a stronger emphasis on quality and lifelong learning will be essential in equipping people to thrive in an AI-augmented world. AI can support such a shift, under certain conditions, by providing personalized learning pathways, identifying gaps in understanding and offering tailored support for students. Broader education reforms can also prioritize critical, creative and systemic thinking. Rather than striving to make AI "better than humans" at various tasks, this approach would help students see AI as a companion—as an enabler that helps people achieve their goals more effectively and efficiently—rather than as a replacement for human skills.

Strengthening AI skills and empowering individuals to engage confidently with AI, in education, in health, in their work, is essential. Rather than perceiving AI as an all-knowing authority that replaces human decisionmaking, people should be equipped to use it as a tool for exploration, learning and creativity. Encouraging an iterative approach—where AI supports problem-solving and enhances human capabilities—can foster confidence and innovation, ensuring that AI is seen as a complement to human intelligence.[300]

As AI continues to race ahead, policymakers, businesses and people are trying to keep pace. However, seizing the opportunities of this new era demands more than technological innovation. An AI-augmented human development framework offers a way forward that is dynamic and can adapt to rapid technological change while being grounded enough to ensure that AI advances translate into meaningful improvements in people's lives.

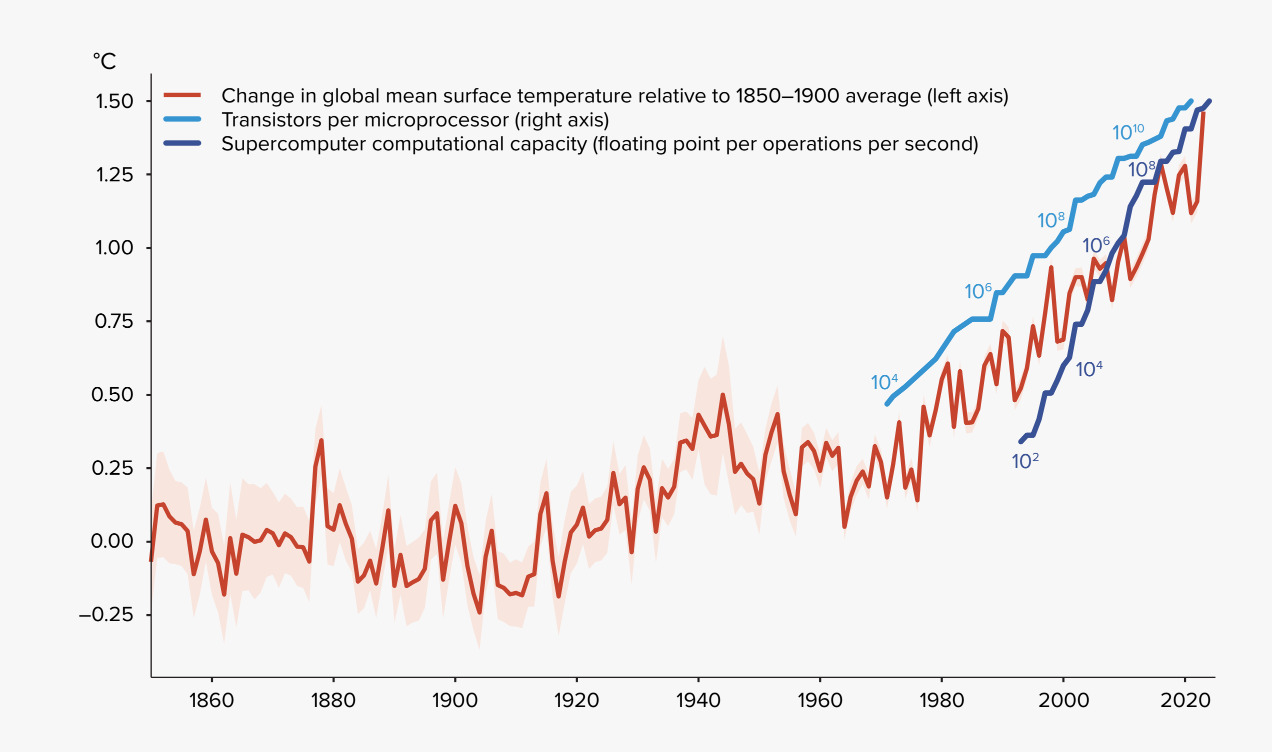
SPOTLIGHT 6.1

The promise and peril of leveraging artificial intelligence to address dangerous planetary change

Although humanity's technological innovations since the Industrial Revolution are the primary sources of Earth-warming emissions fuelling the current climate crisis, scientific breakthroughs have also provided us with the necessary technological tools to perceive, predict and prescribe solutions to the problem. Computing performance has evolved at roughly the same pace as warming temperatures in recent decades, representing a sort of arms race between planetary warming and the capacity for solution-oriented research and innovation (figure S6.1.1).

'One can imagine a hypothetical planet whose atmosphere is more sensitive to the greenhouse effect, whereby global warming and climate destabilization would happen more rapidly following mass combustion of fossil fuels. Had we been faced with the current climate crises, say, 150 years ago, we would have lacked the scientific knowledge, international political apparatuses and technologies needed to solve the problem on a global scale. However, simply having the technological and institutional capacity to solve the issue does not guarantee its solution, as the inadequacy of the current global response has revealed. Although substantial progress has been made to curb global emissions in recent years, we have fallen short of the ambitious Paris Agreement goals to limit

Figure S6.1.1 Computing performance has evolved at roughly the same pace as warming temperatures in recent decades



Source: Data on global mean surface temperature for 1850–1900 from Morice and others (2021), data on transistors per microprocessor from Rupp (2022) and data on supercomputer computation capacity from Dongarra, Luszczek and Petitet (2003).

warming to less than 1.5°C relative to the preindustrial baseline,[1] with the increase in global mean temperature surpassing this threshold in 2024.[2]

Concerted efforts must be made to innovate and deploy technological solutions that leverage the groundbreaking progress in artificial intelligence (AI) and machine learning, along with comprehensive public policies and collective action to mitigate emissions and enable resilient adaptation.

The promise of deploying AI in the Anthropocene

In the electricity sector AI has proven a potent tool for predicting energy markets, reducing operational costs and optimizing grid operations. AI has been used to reduce uncertainty in renewable energy production for a given location by, for example, developing real-time, precise forecasts of cloud cover, identifying dangerous gusts or flocks of birds near wind turbines and improving siting and operational decisions for hydro, geothermal and tidal plants.[3] Better modelling capabilities using AI have also accelerated innovation, leading to safer nuclear fission plants and facilitating breakthroughs in research to harness nuclear fusion.[4]

In addition to improving non–fossil fuel energy production, AI can enable efficiency gains and emissions reductions from traditional, fossil fuel–based sources. Advanced aerial and satellite-based imaging and chemical detection platforms can be paired with AI modelling to pinpoint fugitive emissions from power plants and pipelines. One such example is the MethaneSAT satellite platform, launched in 2024 to hunt for leaking methane—a potent greenhouse gas—from conveyance infrastructure and nonpoint emissions such as agricultural fields.[5] AI models can also improve real-time diagnostics for identifying hazards and system malfunctions to guide preventative maintenance and achieve efficiency gains through the entire electricity grid. This might entail using AI-driven image analysis and weather modelling to identify precise times and locations of high wildfire risk around power lines,[6] optimizing home energy consumption to favour renewable sources.[7] AI can also automate the control of distributed, decentralized and microgrid energy systems to improve grid resilience and energy access in remote areas[8] or optimize grid-scale energy generation for both increased reliability and reduced emissions.[9]

In the transportation sector, which accounts for approximately 25 percent of global emissions, AI helps reduce greenhouse gas emissions through sustainable vehicle design,[10] cleaner materials[11] and improved construction of roads and related infrastructure.[12] It can also help identify optimal policies for reducing transportation emissions sectorwide.[13] Additionally, the abundance of fine-grain, anonymized traveller data from Global Positioning System–based apps allows planners to address regional challenges more precisely and better craft sustainable projects and policy.[14] The design of low-emissions vehicles, such as hybrid-electric and full-electric cars, has also been turbocharged by novel AI applications, as in the discovery of battery materials[15] and greater vehicle range, longevity, safety and fuel efficiency. Autonomous vehicles extensively leverage AI algorithms and sensors for safe self-navigation[16] and design innovation. Electric vehicles and autonomous vehicles can also serve as a unique source of clean power to supplement the grid while they are plugged in. AI helps optimize how vehicle owners can satisfy their charging needs while supplying a distributed source of energy to supplement the grid, improving grid resilience and potentially reducing net emissions.[17]

AI can also facilitate large reductions in building emissions, aiding in the design of energy-efficient construction materials,[18] enhancing local energy demand prediction and improving metering to reduce waste.[19] Cities have employed AI to predict building-scale ratings to target efficiency improvements.[20] "District" heating and cooling networks across neighbouring buildings can offer considerable efficiency gains through economies of scale and have leveraged AI to optimize resource management.[21]

In manufacturing and distribution AI has helped optimize shipping routes to increase delivery speeds and reduce emissions.[22] AI promises to drastically cut manufacturing emissions by accelerating discovery of cleaner manufacturing input materials,[23] optimizing inventory management[24] and aiding in three-dimensional printing of lighter manufacturing components located closer to demand centres.[25] The broad application of three-dimensional printing in manufacturing could reduce global total energy demand by as much as 27 percent by 2050.[26] More accurately predicting variation in markets could enable more precise production, reducing surplus and greenhouse gas footprints.[27] In food shipping, delivery and storage novel algorithms[28] have been used to estimate demand and more accurately predict spoilage, reducing net emissions.[29]

In commercial agriculture AI has improved sustainable tillage practices, precision irrigation, agrochemical application, fertilizer synthesis from thin air[30] and estimation of soil nutrients and crop needs.[31] It has enabled the design of autonomous farm vehicles for more efficient application of inputs[32] and, when applied to remotely-sensed imagery, has enabled finer-scale predictions of crop-water stress,[33] yields[34] and land-based greenhouse gas emissions,[35] which could help reduce global emissions from the agricultural industry.

Managing ecosystems sustainably can also use new AI tools, which have enhanced the ability to quantify natural carbon stocks,[36] improved accuracy in carbon offset markets and closed the balance of the carbon cycle.[37] Advanced computer vision improves assessments of impacts from natural hazards such as floods, droughts, severe storms and fires,[38] allowing for better planning and resilient adaptation. It has also proven effective at tracking human-influenced impacts to the environment, such as deforestation and desertification.[39] Using AI helps approximate the global greenhouse gas budget, especially from uncertain processes such as thawing arctic permafrost,[40] decomposing peatlands[41] and ice sheet melting,[42] improving the accuracy, as well as the computational efficiency, of global climate models.[43]

New AI algorithms have also catalysed numerous breakthroughs in biodiversity monitoring and wildlife biology by revolutionizing the ability to manage, detect, monitor and even interact with animal life.[44] Applied to satellite imagery, classification algorithms have enabled more accurate classification of land cover,[45] habitat loss[46] and assessment of species richness, extent and abundance.[47] They have also enabled more accurate monitoring of changes to critical ecosystems,[48] the spread of invasive species[49] and even the presence of large animals, such as elephants[50] and whales,[51] from space. Using ground-level images, such as those from wildlife cameras[52] or phone-based, citizen science applications,[53] novel AI applications have improved the spatial and temporal granularity of ecosystem monitoring, species detection and migration tracking and have even helped identify illegal poaching.[54]

AI classification tools have improved the identification of specific individuals based on morphological characteristics, such as patterns on whale flukes[55] and primate faces.[56] Algorithms based on animals' audio signatures have allowed for the identification of a habitat's species diversity[57] and the presence and abundance of migratory birds, as well as for the deciphering of species' linguistic patterns.[58] In 2023 scientists claimed to have successfully conversed with an Alaskan humpback whale for 20 minutes,[59] and in 2024 researchers decoded a "phonetic alphabet" used by sperm whales.[60] And one AI-powered phone-based app identifies mosquito species based on the buzz of their wings, alerting the user to the presence of potential disease carriers.[61] Supervised learning algorithms have greatly improved the predictive accuracy of taxonomic habitat assessments when combined with "environmental DNA" sampling methods, whereby the biological composition of a given habitat is estimated based on fragments of genetic material collected from field samples.[62] Researchers have even deployed small aerial drones equipped with AI-backed sensors to glean relevant genetic, hormonal and water quality data simply by collecting mucus from the spray emitted by breaching humpback whales.[63]

The peril of overreliance on technological solutions

While we should embrace all the innovative applications of AI to curb global emissions, improve our scientific models and adapt to evolving hazards, we must not stake all our ambitions for tackling climate change on technological solutions alone. The exponential growth in computing power, climate science and innovation of sustainable technology in recent decades has given us the necessary ingredients to curb emissions and adapt effectively, but the collective political will needed to implement these solutions at scale is lacking. Simply investing in faster computer models and technological development will not solve the problem on its own; political action must be implemented in tandem.

One of the biggest risks of deploying technology aimed at improving energy efficiency and resource consumption without proper oversight is the potential for rebound effects (that is, Jevon's Paradox).[64] Cost savings from more efficient—and marginally cheaper—transportation, agriculture or energy use can increase overall consumption (miles driven, goods produced, energy consumed and the like). Evidence from dozens of studies suggests that economywide rebound effects following energy efficiency gains exceed 50 percent, on average.[65] In other words, striving to improve efficiency alone, without monitoring its impacts on overall emissions, may not be sufficient.

Rebound effects have emerged in AI as well, with recent computing efficiency breakthroughs for advanced large language models offering equivalent performance at a fraction of the prior cost and energy use.[66] But market trends suggest that this will simply boost demand for processing chips and pave the way for bigger, more complex large language models, in turn mitigating the marginal energy savings.[67] The technology sector currently accounts for 2–3 percent of global energy demand,[68] roughly on par with the global airline industry, but as AI computing grows exponentially, so do the greenhouse gas footprints of major companies.[69] The computational demand to fuel AI growth is estimated to double every 100 days,[70] due primarily to the increased energy demand of data centres; the global energy demand for these centres is forecast to increase by 160 percent in the next five years.[71] Water used to cool data centre servers has also increased dramatically and, in some cases, led to local water disputes.[72]

In climate resilience and adaptation AI tools have proven immensely helpful in targeting aid,[73] streamlining data integration[74] and enabling real-time and rapid assessments of impacts and humanitarian needs from extreme events.[75] But staking too much faith on estimates provided by these tools, especially if used in lieu of field-based community assessments of socioeconomic and physical dynamics, can perpetuate bias in reporting and measurement, exacerbate existing inequalities and compromise individuals' privacy.[76] Social protection programmes for vulnerable communities facing acute climate hazards should be expanded, using appropriate new technologies. However, such programmes should continue to be human-centred, with complementary digital tools used equitably, transparently and sustainably.[77]

For biodiversity and ecological monitoring the appeal of new technologies risks diverting attention and limited funding away from traditional field-based research methods and community-oriented participatory stewardship initiatives[78] and reducing direct engagement with local stakeholders in favour of remote, automated data collection.[79] Although AI is expanding the boundaries of ecological monitoring, enabling new research on understudied small, rare and secluded biota,[80] the models ultimately remain limited by the availability of observational data for training, inherently skewing their focus towards regions, habitat types and species where such data are abundant.

Pairing AI climate technology with sound public policy

As pressures on the global climate and ecological wellbeing grow in each passing year, effective solutions to reduce global greenhouse gas emissions, adapt to hazards and conserve sensitive ecosystems are imminently needed. Breakthroughs in intelligent computing have granted us important tools to conceptualize these crises on a planetary scale and will continue to provide critical innovations towards achieving a sustainable and resilient future. But messianic faith and investment in novel technologies alone will not solve the problem. AI in the climate and environmental space will enhance human development and environmental wellbeing only if used in conjunction with broader social policies.

In short, we must want to solve these problems rather than simply innovating new ways to measure them or inventing new products and market efficiencies that are meant—but not guaranteed—to be solutions. If used well, new technologies can be an ace up our sleeve in the fight to safeguard our global environment. If not, they risk serving as false prophets, increasing the fidelity with which we watch planetary pressures progress but ultimately diverting attention away from real solutions—or even making problems worse. The way in which new technology will shape our world is not preordained. As with the impacts of climate change, the impacts of revolutionary new technologies need not represent an inevitable wave of disruption over which we bear no control. Collectively, we have the agency to shape our technology and, ultimately, our planet.

NOTES

1. Allen and others 2018.
2. WMO 2025.
3. Rolnick and others 2022.
4. Aitken and others 2018; Seo and others 2024.
5. Chan Miller and others 2024.
6. Rhizome 2023; Kim 2023.
7. Choi and others 2024; Wolfe 2024.
8. Ali and Choi 2020; Lee and Callaway 2018.
9. Nagapurkar and Smith 2019; Sabzehgar, Amirhosseini and Rasouli 2020; Strezoski and others 2022.
10. Rolnick and others 2022.
11. Madhavaram and others 2024; Pittro and others 2024.
12. Arifuzzaman and others 2021; Kuenzel and others 2016.
13. Abduljabbar and others 2019; Li, Ren and Li 2022.
14. Google Research 2025; Rollend and others 2023; Schewel and others 2021.
15. Ansari and others 2018; IBM 2021; Samuthira Pandian and others 2020.
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40. Ni and others 2021.
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42. de Roda Husman and others 2024.
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51. Cubaynes and Fretwell 2022.
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SPOTLIGHT 6.2

Universal and meaningful connectivity and artificial intelligence

International Telecommunication Union

In 1990, when the first Human Development Report was released, the world counted just 11 million mobile phone subscriptions. These devices were limited to basic calls and text messaging, and the world wide web—the internet, as we know it—did not exist. Today, around two-thirds of the global population uses the internet, and there is almost one mobile broadband subscription per person worldwide.[1] Despite this progress, considerable gaps persist.

An estimated 96 percent of the world is covered by a mobile broadband network enabling access to the internet. But an estimated 32 percent of people do not use the internet, and among those connected, many experience only basic forms of connectivity, with limited speeds and functionality. In least developed countries two-thirds of the population has never used the internet, and millions remain unaware of its existence. Digital divides across geographies and demographic groups—whether between urban and rural areas, genders, generations, education levels or income categories—persist.

For instance, while 51 percent of the world's population is covered by a fifth-generation wireless cellular network, 400 million people still rely on a third-generation network to connect. In rural areas of low-income countries almost 30 percent of the population remains off the grid, with no possibility to connect. Despite falling prices affordability remains a major barrier. In Sub-Sharan Africa people in low-income countries spend about 5 percent of their income for an entry-level mobile data plan—14 times what people in Europe spend. And the average mobile broadband traffic per subscription for an entire month in low-income economies (2 gigabytes) is consumed in less than four days in high-income countries.

Connectivity is not merely about being online. It creates education, healthcare, communication and economic opportunities while fostering creativity, innovation and collaboration.[2] But basic connectivity alone cannot unleash the full potential of the digital world, nor can it support the demands of emerging technologies such as artificial intelligence (AI).

AI systems rely on vast amounts of data and computational resources, both of which are intrinsically linked to connectivity. High-speed internet is essential for transferring and processing the extensive datasets that AI models require for training and operation. Moreover, advanced AI applications, such as natural language processing, image recognition and predictive analytics, depend on cloud computing infrastructure, which itself relies on high-quality, reliable connectivity.

Beyond development, connectivity underpins the practical deployment of AI in ways that can enhance lives. Telemedicine platforms use AI to diagnose illnesses remotely, requiring secure and robust connections to transmit sensitive medical data.[3] Farmers in rural areas access AI-driven tools for crop management and weather forecasting, relying on mobile networks to receive timely insights.[4] Education systems use AI-powered applications to personalize learning.[5]

The current state of connectivity, characterized by deep divides, risks creating a multispeed digital world. In such a scenario a privileged few, equipped with the necessary infrastructure, skills and resources, dominate AI innovation and reap its rewards. At the same time, marginalized communities struggle with limited or no access to the tools needed to participate in this new digital era. Without universal and meaningful connectivity the divides of the analogue world are at risk of being magnified in the digital one.

Recognizing these challenges, the concept of universal and meaningful connectivity has emerged as a critical policy objective. It is defined as enabling everyone to enjoy a safe, enriching and productive online experience at an affordable cost.

Universal and meaningful connectivity does not mean that everyone must be connected all the time. Instead, it is a situation where everyone can access the internet optimally and affordably whenever and wherever needed. Individuals choose how to use this opportunity.

The universal and meaningful connectivity framework has six dimensions: quality (of connection), availability (for use), affordability, security, devices and skills. The dimensions are interdependent; strength in one area cannot compensate for deficiencies in another. Achieving universal and meaningful connectivity thus requires holistic strategies relying on various interventions spanning infrastructure, policies and education and involving different stakeholders. But the framework is deliberately agnostic about specific interventions—investment, policies or regulation—as there is no single pathway and no one-size-fits-all strategy to achieve universal and meaningful connectivity. It is also agnostic about what people use connectivity for—that is, its applications. The neutrality of use cases is paramount: it is impossible to prescribe an ideal digital behaviour.

Since universal and meaningful connectivity was formulated in 2021, it has garnered much attention. In 2022 the International Telecommunication Union (ITU) made it a strategic goal in its 2022–2026 Strategic Plan. In 2023, recognizing the criticality of measurement in achieving universal and meaningful connectivity, the European Union provided the ITU with funding to promote the concept and improve its measurement,.[6] In 2024, under the Brazilian Presidency of the Group of 20, the group's ministers of digital economy adopted a joint declaration committing to achieving universal and meaningful connectivity.[7] The UN Global Digital Compact acknowledges the pivotal role of universal and meaningful connectivity in unlocking the full potential of digital and emerging technologies.[8]

While universal and meaningful connectivity offers transformative potential, one must recognize the dangers of connectivity. Unchecked expansion of the digital sphere can exacerbate issues such as misinformation, digital surveillance and cybersecurity threats.[9] Digital infrastructure, including energy consumption and e-waste, has a major environmental impact.[10] Policies promoting universal and meaningful connectivity must therefore include safeguards to mitigate these risks and ensure that connectivity advances human development.

Just as electricity transformed societies as a general purpose technology, connectivity now plays a similar role. However, its impact on human development hinges on how inclusive and meaningful that connectivity is. As the world seeks to leverage AI and other advanced technologies for inclusive growth, universal and meaningful connectivity represents a policy imperative.

NOTES

1. Unless indicated otherwise, all data in this spotlight are estimates for 2024 from ITU (2024b). See the International Telecommunication Union datahub at https://datahub.itu.int/.
2. ITU 2023b.
3. ITU 2021.
4. ITU and FAO 2021.
5. Khan 2024.
6. ITU n.d.
7. See Digital Economy Working Group and others (2024).
8. See ITU (2023c) and UN (2024).
9. ITU 2023a.
10. ITU 2024a.

SPOTLIGHT 6.3

Global case studies of social dialogue on artificial intelligence and algorithmic management

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Employers are adopting or refining artificial intelligence (AI) and algorithm-based tools in the workplace, with transformative impacts on work and employment.[1] In an International Labour Organization working paper we examined case studies of social dialogue over AI and algorithmic management in different countries and industries.[2] Our analysis suggests that social dialogue is most effective in establishing a more socially equitable and sustainable approach to AI investment when it moves employers towards strategies that take a longer-term view on returns from the investment. This means committing to creating good jobs with benefits and security, sharing productivity gains with workers, investing in skills and worker discretion, limiting invasive data collection and monitoring, and establishing fair and transparent opportunities for workers to challenge and change technology-enabled decisions. Where worker representatives have engaged in social dialogue over AI, they have sought to institutionalize these commitments in collective agreements, laws and policies.

This spotlight summarizes the findings of our analysis of social dialogue cases at the industry and company level. The findings are organized around three action fields in which worker representatives have sought to influence strategies and outcomes associated with the growing use of AI and algorithms in the workplace: social dialogue over the employment and skill impacts of AI, social dialogue over algorithmic management and social dialogue over working conditions and rights in the AI value chain.[3] It concludes with a discussion of three factors that played an important role in supporting successful social dialogue: negotiated or legal constraints on employer exit from employment relationships, institutions and resources that support collective worker voice in organizational decisionmaking and labour strategies based on inclusive forms of solidarity.

Social dialogue over the employment and skill impacts of AI: From labour replacing to labour complementing

New AI- and algorithm-based tools can be applied to automate jobs and tasks in a way that leads to downsizing or replacement of workers and their skills.[4] These tools may also contribute to deskilling work, allowing the downgrading of jobs to more repetitive or lower-value tasks. Alternatively, these tools can complement or augment workers' skills and help them develop new skills and modes of working.[5] Management decisions play an important role in encouraging labour-complementing AI investment—for example, giving workers discretion over how they use tools or restructuring production in a way that creates new, high-productivity tasks.[6]

Through social dialogue labour unions and other worker representatives can encourage employers to use AI in ways that complement and upskill rather than replace and deskill work. Collective agreements can discourage a narrow labour-replacing approach to AI through job and location security agreements, restrictions on permitted uses of AI and rules concerning ownership of and control over creative work and images. For example, in the Republic of Korea the unions at KB Bank led a successful campaign to reverse layoffs of subcontracted call centre workers associated with the increased use of AI chatbots. In Canada and the United States screen writers, actors and journalists have negotiated agreements with rules concerning how AI can be used in writing and editing and disclosure of AI-generated material, as well as protections concerning the use of AI-generated replicas of human performers.

Social dialogue has also actively encouraged labour-complementing strategies by establishing new rules or joint efforts to invest in skills upgrading to improve workers' control over how they apply their skills when using AI-based tools and to share AI-generated productivity gains with the workforce. In Japan social dialogue between the Aeon Group and its labour federation established a productivity improvement subcommittee under a labour–management council to support joint decisionmaking on AI and digital transformation initiatives. Agreements secured job security and redeployment of workers to higher-value-added areas and redistributed productivity gains through wage increases for the majority part-time workforce and for entry-level jobs. In Brazil a national collective agreement in the banking sector included provisions for reskilling in the face of technologies such as AI, with a focus on mitigating gender inequality. Banking employers agreed to finance scholarships for women to take information technology courses, with priority given to women facing socioeconomic vulnerability.

Deutsche Telekom in Germany has one of the most comprehensive agreements establishing both job security and investment in upskilling, underpinned by worker voice. A 2010 agreement states that automation should first be used to reduce subcontracting and commits the employer to train internal employees affected by automation for new jobs. In the mid-2010s the works council organized an eight month project to analyse the impact of new digital and algorithm- and AI-enabled tools on worker skills, jobs and performance. Based on the findings, a series of agreements was negotiated that established a process for ongoing consultation and negotiation over new technologies and their workforce impacts. Management committed to drawing up a digital roadmap with planned digitalization measures and to discussing with the works council the impacts on employment numbers, service quality and work content. This feeds into strategic planning on new agreements for specific technologies.

Social dialogue over algorithmic management: From labour controlling to labour empowering

Management itself is being transformed by AI- and algorithm-based tools. AI is used in predictive or human resources analytics to hire new workers, determine training needs and allocate work. AI is also used to recognize patterns recorded or gathered through diverse electronic data sources to evaluate performance—for example, through AI-enabled cameras, wearable devices and voice recordings applying speech analytics. These tools can be used to intensify surveillance and discipline and to reduce workers' control over the pace and content of their work.[7] They can also contribute to or reproduce biased decisions with considerable employment impacts, such as hiring or firing.[8] At the same time, algorithmic management technologies may empower workers by giving them more control over working methods and schedules or improving transparency in management decisionmaking.[9]

Social dialogue with unions and other worker representatives has focused on reducing the risks associated with intensified control and bias and on improving worker voice in algorithmic management decisions. First, agreements have established baseline workers' rights to data protection and information on how their data are used. Second, they have limited monitoring intensity from new AI-based tools and encouraged the use of performance data to improve skills rather than to discipline workers. Third, agreements have established human-in-command principles, where final decisions on employment-related matters require human oversight, underpinned by AI ethics commitments.

Different combinations of these focus areas can be seen across case studies. For example, IBM Germany negotiated a 2020 agreement on the use of AI systems with its works council that classifies AI applications based on their risk and prohibits the use of AI for automated decisions with immediate effects on employees without human oversight. It also established an AI ethics council made up of AI experts and employer and employee representatives to evaluate AI applications and oversee implementation of the agreement. An agreement in the Spanish banking sector established worker rights to not be subject to decisions based solely and exclusively on automated variables, to nondiscrimination and to request human oversight and intervention. In the United Kingdom an agreement at Parcelforce established that delivery drivers have a right to privacy and that new technology will not be deployed as a disciplinary tool. At UPS in the United States, driver-facing cameras are not allowed, and GPS, telematics and cameras cannot be used as the sole basis for discipline. In the Dominican Republic and

India unions in the business process outsourcing industry have mobilized to improve data transparency and establish limits on the use of AI for sentiment analysis and intensified surveillance. These different agreements place clear limits on the use of high-risk tools while improving transparency and worker trust.

In the United States a 2018 union agreement with 34 Las Vegas casino resorts included a process to bargain over the implementation of new technology. In one example the union used these rights, as well as worker mobilization and innovative data analysis, to challenge and eventually change the use of an algorithm-based app that was used to dictate the room cleaning order to housekeeping staff. In dialogue with the app's developer, the workers and the employer agreed to contract provisions that restored worker autonomy and discretion and made it easier for the union to monitor workload violations. A partnership with the developer and the Culinary Academy of Las Vegas, funded through the union contract, provided training on the software to encourage more effective use of the app. The 2023 contract included rights to privacy from tracking technology, to bargain over technology that tracks employee locations, to notification and bargaining over data sharing with a third party, to healthcare and severance pay for workers laid off due to new technology and to compensation for tipped employees if a technology failure makes it impossible for them to do their job.

Social dialogue over working conditions and rights in the AI value chain: From labour displacing to labour embedding

The AI value chain to produce and refine AI-based technologies has created a new set of jobs in data coding, labelling and engineering that are organized across borders in different countries, often with low pay and tight controls.[10] AI data work is organized through subcontractors that employ workers in physical workplaces and through microwork organized over platforms. It can be described as an example of AI-enabled fissuring, as firms develop more sophisticated AI-based tools to monitor performance and distribute work across a spatially dispersed workforce, organized across vendors, platforms or freelance employment contracts. This in turn permits the displacement of jobs from organizations and employment contracts with established social protections and collective agreements. Different from labour-replacing impacts, in which technology directly replaces tasks or jobs, labour-displacing applications of AI permit organizations to move work to new (often more poorly regulated or lower-paid) contracts, organizations or locations.

The focus of social dialogue efforts in the AI value chain has been to embed or re-embed AI-related jobs in labour and social protections that have been displaced from those protections. Labour union organizing and social dialogue in this area have taken two—sometimes connected—forms. The first relies on solidarity from unions in lead firms, as core technology professionals with more secure contracts seek improved conditions for more precarious contract or platform workers. In the United States unions have organized workers at technology, media and game development firms, including Alphabet, the parent company of Google. One key focus of union action at Alphabet has been improving conditions among the company's more precarious majority temporary, vendor and contractor workforce. Union members have mobilized to support reinstatement, increased pay and benefits, and unionization.

The second form of social dialogue to improve conditions in AI value chains relies on organizing by workers in more precarious AI-related jobs. In Kenya workers who annotate data and moderate content have sought to mobilize to improve conditions. This included bringing legal cases against the subcontractor Sama and its client firms for alleged workers' rights violations, including exploitation, union busting, illegal termination of contracts and pay discrimination. In 2023 a union was formed to represent workers at a range of contract firms that organize AI-related data janitorial services. The union has partnered with local civil society organizations, as well as international organizations working to create ethical standards for AI deployment. These initiatives aim to influence policies at the national and international levels, including transparency, fair compensation and protections against algorithmic exploitation.

Conclusion

The findings demonstrate a range of creative AI-focused social dialogue initiatives across three action fields: skills and employment, algorithmic management and working conditions in AI value chains. Three factors played an important role in supporting these initiatives: negotiated or legal constraints on employer exit from employment relationships, institutions and resources that support collective worker voice in organizational decisionmaking and labour strategies based on inclusive solidarity.[11]

In the cases reviewed, strong employment protections and skill investment were central goals that made it more difficult or less desirable for firms to exit their internal workforce through downsizing, deskilling or outsourcing. Laws establishing clear rules and copyright protections on the use of generative AI to reproduce art, voice or images are one example. Collective agreements across countries provided job security, commitments to decrease subcontracting or support for retraining and redeploying workers.

Support for collective worker voice took different forms. Strong participation rights and laws, unions and tripartite social dialogue traditions were critical resources for negotiating AI-focused agreements. Data protection laws and agreements were used to limit worker surveillance and provide information on what data were collected on workers or how the data were used. And bright line prohibitions of certain uses of AI to automate human resources decisions or of sentiment analysis tools could help establish more transparent workplace rules. In many cases worker mobilization, sometimes through strikes, were crucial in bargaining to establish or extend protections to AI-based tools.

Finally, strategies of inclusive labour solidarity helped ensure that the most vulnerable workers in easily rationalized or monitored jobs were included in social dialogue efforts. The negative impacts of AI bias and invasive algorithmic management practices are heavily concentrated among workers who also tend to hold more precarious contracts. Labor solidarity has been crucial in AI value chains for extending bargaining power and building a strong movement of workers in more and less precarious engineering, programming and data labelling jobs.

These three factors—constraints on employer exit, support for worker voice and strategies of inclusive labour solidarity—were present in different combinations across the case studies of social dialogue on AI. However, worker representatives in these cases also sought to strengthen minimum standards and worker voice in decisionmaking by establishing new laws, policies and collective agreements. These solidaristic organizing and mobilization efforts are an important first step in promoting alternative high road approaches to AI investment that are designed by the workers most directly affected by the technologies.

NOTES

1. AI refers to computer systems that can perform tasks traditionally requiring human intelligence, including advanced pattern recognition and problem solving (Russell and Norvig 2021.).
2. The case study examples in this spotlight are from our International Labour Organization Working Paper (Doellgast and others forthcoming), where they are described in more detail. We use the International Labour Organization's definition of social dialogue, which includes "all types of negotiation, consultation or simply exchange of information between, or among, representatives of governments, employers and workers, on issues of common interest relating to economic and social policy. [….] Workplace cooperation, collective bargaining at company, sector or cross-industry levels, and tripartite consultation processes are common forms of social dialogue" (ILO 2025).
3. Doellgast 2023.
4. Eloundou and others 2024; Frey and Osborne 2017.
5. Gmyrek, Berg and Bescond 2023.
6. Acemoğlu and Restrepo 2020; Zysman and Nitzberg 2024.
7. Rani, Pesole and Vázquez 2024.
8. Ajunwa 2023.
9. Jarrahi, Möhlmann and Lee 2023.
10. Muldoon, Graham and Cant 2024.
11. Doellgast 2022.

Notes and references

Notes

OVERVIEW

1 The belief that virtually any problem has a technological solution.

2 Hoffman and Beato (2025) provide a perspective on the opportunity side of AI if it is designed for human agency.

3 Galaz 2025.

4 The United Nations Development Programme survey on AI and Human Development is one of the world's largest public opinion surveys on AI in the past three years. From November 2024 to January 2025, more than 21,000 people in 21 countries and 36 languages were surveyed, representing 63 percent of the world's population. These 21 countries were selected to provide results covering different Human Development Index groups and regions of the world. The survey primarily employed randomized telephone polling to ensure broad reach across varied populations (with web polling used in two countries). The 19 questions in the survey capture how AI is influencing daily life, shifting decisionmaking power and redefining public confidence in technology.

5 The very high HDI threshold value is 0.800.

6 The loss of steam in global progress could indicate a lower trend going forward. Health indicators, particularly life expectancy at birth, are increasing more slowly, with an annual increase of about 0.130 a year for 2023–2024, compared with 0.267 a year for 1990–2019. This slower trend for life expectancy at birth is projected to continue in the coming decades (2025–2050). The world could have attained very high HDI status by 2030 if global HDI values had continued to follow the pre-2020 trend. However, based on the 2021–2024 trend, achieving very high HDI status has been postponed by three years, to 2033. If the 2023–2024 trend persists, the delay may extend to three decades.

7 Rodrik and Sandhu 2024; Stiglitz 2021.

8 Rodrik and Stiglitz 2024.

9 Acemoğlu, Autor and Johnson 2024; Autor 2024; Rodrik and Stiglitz 2024.

10 Ludwig and Mullainathan 2024.

11 Huang and others 2025; Li and others 2023.

12 Acemoğlu and Johnson 2023.

13 Autor 2022; Baily, Brynjolfsson and Korinek 2023; Bresnahan 2024; Brynjolfsson 2022b; Korinek 2024; Manyika and Spence 2023.

14 This is a simple unweighted average; each country's average response carries equal weight.

15 Among respondents who expect AI to change their jobs, the majority expect both augmentation and automation. Among respondents who expect only either augmentation or automation, roughly twice as many expect augmentation as expect automation.

16 See, for example, Conboye (2025), who found that close to 60 percent of respondents under age 35 in China, Indonesia and Peru said that AI would make their job better in the next five years, compared with less than 30 percent in Canada, Japan and the Republic of Korea, based on data from the 2024 Ipsos AI Monitor (Carmichael 2024).

17 Cui and Yasseri 2024.

18 For example, addressing AI biases in health applications requires better algorithms and data, but coding alone will not redress biases (Marwala 2024). This in part because biases require constant attention and monitoring, given that fairness considerations are context specific and dynamic (Mienye, Swart and Obaido 2024).

19 Adapa and others 2025; Dangi, Sharma and Vageriya forthcoming; Zuhair and others 2024.

20 Labadze, Grigolia and Machaidze 2023.

21 Alzate 2023; Pedro and others 2019; Vincent-Lancrin and Van der Vlies 2020.

22 Drolia and others 2022; Government of Mexico 2020.

23 Blanchflower 2021.

24 Blanchflower, Bryson and Xu 2024.

25 Blanchflower 2025.

26 Thiagarajan, Newson and Swaminathan 2025.

27 Thompson 2024.

28 Touzet 2023.

29 Consider Google Relate, a free mobile application that can support communication between people with communication disabilities and strangers. Making it work well is contingent on changes in communication norms—through, for instance, greater acceptance of diverse ways of communicating. Speech recognition can change the dynamic of the conversation, including adding pauses and altering the flow of an exchange. If the other person in the conversation does not understand or refuses to accept these "new rules," the interaction will fail (Ayoka and others 2024).

30 Deep gender gaps in the use of generative AI persist even when access to AI is enhanced (Otis and others 2024).

31 Brynjolfsson 2022a; US National Academies of Sciences and Medicine 2024.

32 Autor 2024.

33 Autor and others 2024; Crafts 2021b; Ernst, Merola and Samaan 2019.

34 Bastian and others 2024; Higgins and others 2021; Liu and others 2024.

35 Hatherley 2020.

36 Dvijotham and others 2023.

37 Brynjolfsson, Li and Raymond 2025.

38 Noy and Zhang 2023.

39 Peng and others 2023.

40 Dell'Acqua and others 2023.

41 Agrawal, Gans and Goldfarb 2023; Kanazawa and others 2022. See also Kanazawa and others (2022). Whether these sector-specific effects extend to the whole economy is unknown as of now.

42 Babina and others 2024.

43 Wilson, Daugherty and Bianzino 2017. Explainer calls for translational expertise, so that outputs from AI can be evaluated and assessed before being incorporated into decisionmaking. AI hallucinations and human-AI miscommunications are certain to create value for having a human with "skin in the game" somewhere between prompt and implementation. Trainer encompasses new tasks such as prompt engineering and retrieval-augmented generation. Having AI accomplish tasks for humans, making the most out of AI, will require humans writing prompts and customizing models for domain-specific applications—already on ChatGPT there are hundreds of thousands of domain-specific applications created by humans (Korinek and Vipra 2024). Sustainer encompasses tasks associated with keeping up with AI progress and ensuring that both skills and organizational processes make the most of the opportunities as they evolve over time. In the example above radiologists have taken on the tasks of explainer and sustainer, even as AI has augmented the task of diagnosis.

44 J-PAL 2023; Lipowski, Salomons and Zierahn-Weilage 2024.

45 UN and ILO 2024.

46 UN and ILO 2024.

47 For example, Cazzaniga and others (2024) find that higher educated workers in high-income economies are better positioned to harness generative AI for work augmentation

and have more access to and an easier time transitioning to roles where generative AI is likely to enhance their work.

48 Gmyrek, Winkler and Garganta 2024.

49 Acemoğlu and Johnson 2023.

50 To be clear, the argument is about complementarity between humans and AI in the creative process, not replacing human creativity with machines, which even if it were feasible, would not be desirable from a human development perspective.

51 Cockburn, Henderson and Stern 2019; Crafts 2021a; US National Academies of Sciences and Medicine 2024.

52 Binz and others 2025; Delgado-Chaves and others 2025; Luo and others 2024; Musslick and others 2025.

53 Along the lines of the complementarity between humans and AI discussed in Felin and Holweg (2024). See also Dubova, Galesic and Goldstone (2022).

54 Adam 2023; Epstein and others 2023. For example, AI that defeated humans at games such as chess by learning to play the games themselves is now inspiring chess grandmasters with nonhuman moves that make them more creative (Schut and others 2025).

55 Acemoğlu 2024.

56 Eriksson and others 2025.

57 Wang, Hertzmann and Russakovsky 2024.

58 Schmid and others 2025.

59 Dennis 2024.

60 Esmaeilzadeh (2024) report an ongoing cultural shift in healthcare, with AI being increasingly viewed as a delivery enhancer and job creator rather than as a threat.

61 Perhaps analogous to the way that pharmaceuticals are deployed and monitored, as suggested in Belenguer (2022).

62 Consider the seminal works in economics by, for example, Romer (1994, 1990) and Solow (1956), who show that productivity growth hinges on knowledge and technological change.

63 Johnson and Acemoğlu 2023.

64 Verhoogen 2023.

65 Diouf and others 2024; Mishra and others 2023.

66 Wei, Jörg and Rolf 2024.

67 Allen and others 2025; Shahriar and others 2025.

68 Swartz, Denecke and Scheepers 2023; Walton 2022.

CHAPTER 1

1 Mitchell 2025.

2 As explored in Korinek and Suh (2024).

3 Bengio and others 2024; Harari 2024; Müller and Bostrom 2026; Ord 2020. There is wide disagreement about the extent to which AI poses existential risks, with experts unable to agree even on what kind of evidence would suggest whether those risks may emerge or how likely they would be (Rosenberg and others 2024). On the potential tradeoffs between leveraging AI for growth and addressing possible existential risks, see Jones (2024), who finds that if AI reduces mortality, it would still make sense to take existential risks (see also C. I. Jones 2025). One concern is that AI can self-replicate without human intervention, with some studies suggesting that this frontier may have already been surpassed (Pan and others 2024). However, using AI to improve AI is already widely practiced; it actually extends to the pre-AI era of software development. Narayanan and Kapoor (2024b) argue that what gives humans power is not intelligence as such but our ability to work together with technology, so more-powerful technology makes us more, not less, powerful. In addition, there are technical challenges in being able to estimate AI-related risks, as reviewed in Narayanan and Kapoor (2024a).

4 For a comprehensive review of the state of AI and its future at the time of writing, see AAAI (2025), and for a media summary, see B. Jones (2025). Evidence suggests that one gap in AI adoption is a lack of understanding of its capabilities and limitations (see Cucio and Hennig 2025 for the case of the Philippines).

5 This is inspired by Narayanan and Kapoor (2024b, p. 285).

6 Bradford 2023; Bradford, Waxman and Li Forthcoming; Lang and others 2024; Olson 2024; Suleyman 2023.

7 Bengio and others 2025; Gerundino and others 2024; UN 2024.

8 See the B-Tech project from the United Nations Office of the High Commissioner for Human Rights, which provides guidance into the regulation and operation of technology companies, grounded on the UN Guiding Principles on Business and Human Rights (https://www.ohchr.org/en/business-and-human-rights/b-tech-project).

9 Hoffman and Beato (2025) also provide a perspective on the opportunity side of AI if it is designed for human agency.

10 The lack of productivity gains from just substituting one general-purpose technology with another while keeping everything else the same occurred when electric motors became available in the late 19th century. When factories simply replaced steam-powered engines, the expensive switch did not yield any productivity gains, and many firms decided not to adopt the new technology. (Interestingly, the same delay happened when steam power became available in the early 19th century, and many factories decided not to replace waterpower: while steam power became available around 1830, by the beginning of the 20th century, only 40–50 percent of US mills had adopted it; Hornbeck and others 2024). It was not until several decades later that a reorganization of production harnessed the potential of electric motors. In this reorganization multiple electrical motors were attached to each machine in a factory spread out horizontally on a single floor. This replaced steam-engine production in which a factory used only one source of power in a tall building, with machines linked to that single source of power through shafts and cables (David 1990).

11 Declining production costs due to technological innovation tend to translate into higher net income for consumers, and technological innovation improves welfare through, for example, hedonic effects, which are no less real for being difficult to measure. We are grateful to David Zuluaga Martínez for suggesting these mechanisms at play.

12 Nordhaus 2004. The study refers to the US economy and estimates that between 1995 and 2000 new digital firms appropriated only $400 billion of the $6 trillion increase in social value created by digital firms and that investors' overestimates of the extent to which firms could appropriate innovations might have led to the rapid increase in stock market valuations and subsequent collapse (the so-called tech bubble) of the 1990s. Adding new features such as a camera to a smartphone generates value to consumers an order of magnitude greater than what they pay (Brynjolfsson and others forthcoming). See also Brynjolfsson, Kim and Oh (2024).

13 Brynjolfsson and others 2023. The lower share in very high HDI countries is consistent with results from other surveys showing higher expected AI use in middle-income countries.

14 The United Nations Development Programme survey on AI and Human Development is one of the world's largest public opinion surveys on AI in the past three years. From November 2024 to January 2025, more than 21,000 people in 21 countries and 36 languages were surveyed, representing 63 percent of the world's population. These 21 countries were selected to provide results covering different HDI groups and regions of the world. The survey primarily employed randomized telephone polling to ensure broad reach across varied populations (with web polling used in two countries). The 19 questions in the survey capture how AI is influencing daily life, shifting decisionmaking power and redefining public confidence in technology. "

15 Close to 60 percent of respondents under age 35 in China, Indonesia and Peru said that AI would make their job better in the next five years, compared with less than 30 percent in Canada, Japan and the Republic of Korea (Conboye 2025 using data from Ipsos AI Monitor 2024 for 32 countries; https://www.ipsos.com/en-us/ipsos-ai-monitor-2024).

16 Autor 2022; Baily, Brynjolfsson and Korinek 2023; Bresnahan 2024; Brynjolfsson 2022; Korinek 2024.

17 On the narrowing of past development pathways and the need to reinvent new approaches, see Rodrik and Sandhu (2024) and Stiglitz (2021). On the historical importance of manufacturing in creating jobs at scale, particularly for low-skilled workers, and in driving economywide productivity growth, see Rodrik (2012). On the role of manufacturing in reducing poverty, see Erumban and de Vries (2024). Part of the appeal of manufacturing is that

the products are tradable, so some—though not all—of the advantages of manufacturing could be extended to tradable services (Inklaar, Marapin and Gräler 2024). To leverage tradables, it is important to be able to export to international markets to avoid being constrained by (potentially small) domestic markets; see Goldberg and Reed (2023).

18 Diao and others 2024; Rodrik 2015; UNCTAD 2024. On how the transition to services unfolded in India, see Fan, Peters and Zilibotti (2023). Kruse and others (2023) report an increase in manufacturing in some low- and middle-income countries but still conclude that further employment opportunities in manufacturing are likely to be constrained by automation, which is the key point that will be elaborated later in the chapter. Herrendorf, Rogerson and Valentinyi (2022) show that, contrary to what is often assumed, productivity in services is higher in low- and middle-income countries than in high-income countries, unlike productivity in both agriculture and services, which is lower and showing increasing gaps. Chen and others (2023a) show that since 2005 productivity increases in China have been higher in services than in manufacturing. On how structural transformation can unfold without industrialization, see Jing and Foltz (2024) for Côte d'Ivoire and McCullough (2025) for Tanzania.

19 Acemoğlu, Autor and Johnson 2024; Autor 2024; Rodrik and Stiglitz 2024.

20 Caballero and others (2025) provide a compelling illustration that digital innovation on its own does not improve access to credit in small firms in emerging economies.

21 Bresnahan 2024; Gollin and Kaboski 2023.

22 Computational machines are those able to access, process and act on abstract information (Brynjolfsson and Hitt 2000; US National Academies of Sciences and Medicine 2024).

23 Following Sendhil Mullainathan and colleagues (Ludwig, Mullainathan and Rambachan 2025).

24 For example, the large language model that powered GPT-4 initially achieved only 4.3 percent accuracy in multidigit multiplication (Yang and others 2023b). A "smart" machine fails at something in which a dumb pocket calculator achieves 100 percent accuracy because of the inherent differences between AI and earlier digital tools, as explored in the chapter. For a feisty account of the reasons why large language models have failed on basic arithmetic, see Marcus (2023). Despite ongoing improvements, numeracy gaps in large language models remain pervasive (Li and others 2025). This does not mean that large language models cannot improve at the tasks they are not good at. For instance, much effort has been deployed to improve mathematical "reasoning" in large language models (Ahn and others 2024) and better understand the reasons for persistent limitations (Feng and others 2024; Shrestha, Kim and Ross 2025).

25 Cave and Dihal 2019; Craig and others 2018; Mitchell 2023b, 2024a, 2024b.

26 For a fascinating application of AI to enhance teaching of Tang poetry, see Chen and Wu (2024). For a more general discussion of AI's potential to advance art, along with some of the emerging risks, see Epstein and others (2023). Other examples include how AI can enhance design (Jiang and others 2024; Zhu and others 2018), writing (Hitsuwari and others 2023; Wang and others 2024e; Yuan and others 2022), music (Doh and others 2023; Ding and others 2024; Gardner and others 2023), humour (Wu, Weber and Müller 2025) and interpretation of literary metaphors (Ichien, Stamenković and Holyoak 2024).

27 Since 2017 AI such as AlphaZero has been shown to consistently beat any human at the game (Silver and others 2018). But subscribers to chess.com have increased more than fivefold since then, from 20 million in 2017 to 100 million in 2022 (https://www.chess.com/article/view/chesscom-reaches-100-million-members). AI has driven this renaissance of interest in chess, in part by creating more opportunities for people to play the game, train and get better at it when they play with other humans (Gaessler and Piezunka 2023). See also Machajewski (2024).

28 For evidence that streaming stimulates demand for live music, see Christensen (2022). In 2024 global streaming revenue reached $20 billion, up from $13 billion, and performance rights reached $3 billion in 2020, up from $2 billion (IFPI 2024). More broadly, there is often complementarity between physical and digital goods. For instance, the digitalization of books has increased demand for hard copies (Bhuller and others 2024).

29 Korinek 2024.

30 Lazar 2024b.

31 Brynjolfsson, Mitchell and Rock 2018; Gathmann, Grimm and Winkler 2025.

32 Lazear and others (2022) articulate key differences for productivity and wages between the digital world before and with AI.

33 Acemoğlu and Johnson 2023.

34 Manyika and Spence (2023) discuss how AI could unleash an economic revolution that would trigger productivity growth.

35 Acemoğlu and Restrepo 2019c.

36 Gray and Suri 2019; Muldoon, Graham and Cant 2024; Muldoon and others 2024. Impacts vary across the world, with workers in places with weaker labour regulations or institutions such as trade unions more vulnerable (Doellgast 2023). One harmful implication relates to the deterioration of psychological wellbeing in content moderation workers (Gonzalez and Matias 2025; Steiger and others 2021).

37 Creutzig and others 2022; Galaz 2025. For the challenge of AI-related e-waste, see Wang and others (2024c). These challenges are exacerbated as the scale of the AI models increases (Varoquaux, Luccioni and Whittaker 2024).

38 Hager and others 2024; Singhal and others 2023; Singhal and others 2025. AI can already fulfil the requirements to get an engineering degree (Borges and others 2024) and pass the uniform bar examination in the United States (Katz and others 2024), but that is different from having AI do what engineers do (Xu, Kotecha and McAdams 2024) and lawyers (Kapoor, Henderson and Narayanan 2024; Socol de la Osa and Remolina 2024).

39 Garassino and others 2025.

40 For example, people with no experience with computer programming can now create apps and other software from scratch just by describing in normal spoken language what they want the tools to achieve—something that has been called vibecoding (Rose 2025).

41 For example, as of mid-March 2025, almost half of large-scale large language models have published and downloadable weights (the numbers in the neural network that reflect the machine's learning), offering much flexibility in customizing these models (https://epoch.ai/data/large-scale-ai-models). A mid-February 2025 account describes the previous month as "one of those months where it feels like a year passes in the open-source ecosystem," presenting multiple examples of open-source datasets and AI models (Lambert and Brand 2025).

42 Farrell and others 2025.

43 Mutiso 2025; Nuwer 2024; Signé 2025. At the same time it should not be seen as a panacea (Krishna 2024).

44 OECD 2025.

45 Korinek 2024.

46 Acemoğlu and others 2023; Das, Amini and Wu 2025; Gadotti and others 2024; Goldfarb and Que 2023.

47 Ludwig and Mullainathan 2024.

48 And if it were able to make accurate predictions, there might be moral reasons to object to having people subject to AI predictions (Lazar and Stone 2024).

49 Narayanan and Kapoor 2024b; Wang and others 2024a. Moreover, what Neumann and others (2024) called data deserts implies risks of underrepresenting low-income segments of the population.

50 We are grateful to David Zuluaga Martínez for this point.

51 Volokh 2023.

52 Browne and others 2023.

53 Guerreiro and others 2023; Huang and others 2025; Li and others 2023.

54 Caplin 2025a. The deviations may even extend upstream, given that AI is trained on human data (Treiman, Ho and Kool 2024).

55 These choices influence decisions ranging from the direction of AI, its use to either automate or augment tasks by firms and how people interact with AI (Brynjolfsson 2022; Korinek 2024; Korinek and Stiglitz 2018, 2020; Trammell and Korinek 2023).

56 Summerfield (2025) describes large language models as "strange new minds."

57 Sejnowski 2023, p. 311.

58 Frank 2023; Karell, Sachs and Barrett 2025; Mei and others 2024; Mitchell 2023a, 2024a; Mitchell and Krakauer 2023; Shiffrin and

Mitchell 2023; Trott and others 2023. There are efforts to characterize the psychological profiles of large language models (Pellert and others 2024), including based on whether they are able to mirror humans' theory of mind—that is, people's ability to infer other's mental states (Shapira and others 2024; Strachan and others 2024). And their behaviour as economic agents (Fontana, Pierri and Aiello 2024) considers how different large language models play the prisoner's dilemma game. Chen and others (2023b) document the emergence of economic rationality, and Raman and others (2024) propose a benchmark to assess that rationality. These debates and efforts will continue to guide the evolution of AI as a science and as a technology, in the same way that Herbert Simon challenged the scientific community many years ago to build a machine that could beat humans at chess (Simon 1971).

59 Vallor (2024), along the lines also argued in Krakowski (2025). Evidence at the firm level shows that AI adoption will involve both automating and augmenting tasks (Krakowski, Luger and Raisch 2023; Raisch and Krakowski 2021).

60 Agrawal, Gans and Goldfarb 2024b.

61 Valenzuela and others 2024. del Rio-Chanona, Laurentsyeva and Wachs (2024) found that since the emergence of large language models, there has been a 25 percent decline in online fora such as Stack Overflow, where programmers share knowledge and solve problems. Beane (2024) emphasizes the importance of having mentors and human relationships between novices and experts as part of learning, even if large language models can help with ready solutions.

62 Doshi and Hauser 2024; Kleinberg and Raghavan 2021.

63 Awad and others 2018; Bonnefon, Rahwan and Shariff 2024; Purcell and Bonnefon 2023; Vallstrom 2024.

64 Barnes, Zhang and Valenzuela 2024. Even aspects such as alignment with human values (Globig and others 2024) and hallucinations need to be evaluated in a culturally sensitive way (McIntosh and others 2024).

65 Goethals and Rhue 2024; Mazeika and others 2025; Zewail and others 2024.

66 Boulus-Rødje and others 2024.

67 This is particularly critical in some tasks where building skills implies engaging in activities such as writing, which develops skills in argumentation, critical thinking and attention to detail. Leveraging AI to augment human intelligence in the context of writing requires it to not only help people express ideas in the moment but also develop those skills in the long term (Stuhler, Stoltz and Martin 2023; Yan and others 2024). This will require responding on the supply side as well, by building machines that learn and think with people and are promoted as such (Collins and others 2024b).

68 Mitchell (2021, 2024b) has warned that anthropomorphic language shapes people's relationship with the technology (for instance, whether they trust it), as well as how it is viewed both scientifically and by decisionmakers. Deroy (2023) and Dorsch and Deroy (2025) go further and question the ethics of using anthropomorphic language with respect to AI.

69 Hinton 2016. For a video, see https://www.youtube.com/watch?v=2HMPRXstSvQ&t=29s.

70 An economically coherent and possible scenario described in Nordhaus (2021).

71 In general, it might be difficult to extrapolate AI advances tested on abstracted versions of real-world problems to their effects in the real world. Foundational AI efforts such as those that Geoffrey Hinton pioneered are crucial and were recognized with a Nobel Prize in 2024, but real-world applications are not determined alone by how well the models perform theoretically or in more circumscribed domains. We are grateful to Zi Wang for this insight.

72 D'Souza and Davis 2024. See also Henderson (2022). Ironically, the increase in demand for radiologists stems in part from medical images becoming more abundant and more accessible with AI, generating more demand across a range of healthcare professionals.

73 A task-centred rather than job-centred approach seems helpful to explore AI's impact on the world of work. Bonney and others (2024a) find that about 27 percent of US firms using AI reported impacts on tasks, but only 5 percent reported employment (job-level) changes.

74 According to the International Standard Classification of Occupations, the occupation of radiologist involves more than 12 tasks, including interacting with patients and other medical professionals; conducting specialized diagnostic tests is only one (see the entry for Unit Group 2212 in ILO 2012). According to the Occupational Information Network, radiologists perform 30 different tasks (see https://www.onetonline.org/link/summary/29-1224.00).

75 Dranove and Garthwaite 2024.

76 On the benefits in lower income countries and settings, see Khosravi and others (2024) and Tanno and others (2024). Agarwal and others (2023) document the challenges of human–AI interaction in radiology and the potential need for new tasks and expertise by radiologists. Awuah and others (2025) show how AI imaging models are being combined with other AI tools to improve prognostic accuracy for people with malignant gliomas, one of the most aggressive primary brain tumours, demonstrating how deploying AI for imaging complements the use of other AI tools. For broader applications of AI, including but going beyond support with medical images, and how these supplement rather than replace radiologists, see Bhandari (2024).

77 Acemoğlu and Restrepo (2018, 2019b) formalized the framework for how introducing machines can lead to both task displacement and task reinstatement. For a recent review, see Restrepo (2024). It has been used to interpret trends in economic inequality (Acemoğlu and Restrepo 2024) and to consider the introduction of AI (Acemoğlu and Restrepo 2019a, 2019c).

78 In one study overall reading times were shortened, but when AI detected abnormalities, reading times increased (Shin and others 2023). For reasons discussed later in the chapter, the nature of AI implies that the interaction between radiologists and AI is more nuanced, with heterogenous effects across different radiologists (Yu and others 2024).

79 In addition to the analysis of tasks, it is important to determine whether a price reduction leads to more demand overall, which depends in part on how responsive demand is to the decline in price—what economists call the price elasticity of demand. When productivity improves in a sector, making more with less does not mean that there will be less labour demand in that sector (let alone in the economy as a whole): even if each clinic sees less demand for radiologists because of productivity gains, cheaper radiology services may increase overall demand for more clinics. Think of what happened with air travel when jet engines replaced propellers. Pilots became much more productive and air travel much cheaper, and the sector's high price elasticity led to a boom in demand for pilots. This example draws from US National Academies of Sciences and Medicine (2024). The elasticities are generally low for healthcare but higher for radiology than for other health services (Ellis, Martins and Zhu 2017).

80 There are other far-reaching implications of using AI to help radiologists. AI expands human development by making it feasible to extend cancer screening and other radiology diagnostics to low-income countries where it was difficult to do so before machine-assisted medical imaging was available (Zuhair and others 2024). Deploying AI to help with medical imaging also calls for community health workers trained to support the deployment, increasing the demand for labour in local communities (Adapa and others 2025; Dangi, Sharma and Vageriya forthcoming; Zuhair and others 2024).

81 Svanberg and others 2024.

82 Kaufman and others 2025. Data for the United States are from the RAND American Teacher Panel.

83 Conboye 2025. For details on the survey, see https://www.adeccogroup.com/global-workforce-of-the-future-research-2024. Workers were able to save time using AI; the top two tasks where time was saved were checking work quality and accuracy and engaging in more creative work. In the United States worker use of AI is much higher than firm adoption of AI (for workers, see Bick, Blandin and Deming 2024; for firms, see Bonney and others 2024b). Another survey found that the number of employees using AI for a third or more of their work was three times as high as their leaders imagined (Mayer and others 2025). A survey of US firms from before generative AI was introduced found that adoption was comparable to current use, at around 5 percent (McElheran and others 2024), but is now growing rapidly (Bonney and others 2024b).

84 Bandiera and others 2022.

85 For a 200 year analysis, see Kogan and others (2021, 2023). For a more narrowly focused study of the adoption of industrial robots between 1993 and 2014, see Lerch (2025).

86 Babina and others (2024) find little impact of AI on cost reductions in US firms. Zhai and Liu (2023) find the same in Chinese firms. Thus, firms that increase AI investment exhibit higher growth in sales, employment and market valuations, but this is achieved primarily through increases on the revenue side rather than reductions on the cost side.

87 Bonney and others 2024a, 2024b.

88 Eisfeldt, Schubert and Zhang (2023) report that firms exposed to AI increased their valuation. Further analysis showed evidence that generative AI's impact on those increases occurred through labour displacement (Eisfeldt and others 2024). Already, the diffusion of generative AI is depressing employment and earnings for some workers, including freelance workers on an online platform engaged in tasks ranging from data entry and graphic design to software development (Hui, Reshef and Zhou 2024). Analysis of earnings calls of listed US firms revealed a sharp increase in positive sentiment about AI after ChatGPT was released in November 2022. And while references to new products are part of this optimism, so are expectations for increased efficiency (Bass and others 2024).

89 Historically, technological progress often hurt incumbent workers, and it was not until (sometimes new) institutions reshaped incentives that workers benefited from technological change (Acemoğlu 2025; Acemoğlu and Johnson 2023; Scott Morton 2024).

90 Narayanan and Kapoor 2024b.

91 More rigorously, this corresponds to a move from special-purpose computational machines to general-purpose computers, corresponding to the implementation of the theoretical concept of a Turing machine from computer science (see spotlight 1.2 for details).

92 Potentially in many of the world's natural languages (Barrault and others 2025; Costa-jussà and others 2024).

93 Hephaestus, the Greek god of invention, created a bronze giant called Talos (Mayor 2018). Talos's tasks were immutable and externally imposed, a stark contrast from the dynamic and intrinsic motivations that guide human action. Talos's tale is a reminder of both our quest for automation and our understanding that machines can accomplish human tasks without being human.

94 Reid-Green 1989.

95 Not to be misunderstood as something different from quantum computing but simply to refer to machines that execute prespecified programs, which can also be implemented using quantum computing. US National Academies of Sciences and Medicine (2024) uses the term classical computing to refer to the second stage; the use of classical programming is meant to make it clear that the contrast is not between quantum and nonquantum computing.

96 Hoffmann and others 2024; Mannuru and others 2023; Yang and others 2024. It is costly (more than $100 million) to rough out such a machine on oceans of laboriously collected and curated data. Further human effort—often exploitative—fine-tunes large language models such as ChatGPT, Claude, DeepSeek and Gemini (Cottier and others 2024). In a sense we are in the early days and will surely observe multiple ancillary breakthroughs that redefine how these machines are instructed and their tasks delegated. But the framework of higher generality (executing an ever-wider range of tasks) with lower human effort focuses on the essential features of each stage.

97 McElheran and others (2024) show that even in the United States AI adoption around 2018, while pervasive across sectors of the economy, was concentrated in firms in a few cities and in young firms led by highly educated owners overrepresented in AI adoption.

98 Narayanan and Kapoor 2024b, pp. 147, 166.

99 Bick, Blandin and Deming 2024.

100 The aspiration to achieve artificial general intelligence may have driven scientific progress in the field, akin to Herbert Simon's challenge to build a machine that could beat humans at chess, but it is no longer universally seen in the scientific community as a desirable north star (AAAI 2025; Blili-Hamelin and others 2025).

101 The same choices may not be made across all domains, cultures and contexts. And some tasks are not ends in themselves but means to ends—for example, learning. Those considerations, rather than whether a machine surpasses what humans can do, are what matters for human development.

102 There is no neutral way to advance technological progress, so being explicit about what is desirable matters (Acemoğlu and Johnson 2023). Others may have different goals, including, from a scientific perspective, ways to measure machine capabilities on a range of technical benchmarks for how close we are getting to artificial general intelligence.

103 Up to consistent errors based on programming logic.

104 Autor 2019; Autor, Levy and Murnane 2003.

105 For example, automated teller machines automated both cognitive tasks (verifying card details, processing transactions) and manual tasks (dispensing cash). Despite automating routine cognitive labour, they did not eliminate bank clerks or bank branches. As with radiologists, their occupations persisted, as many tasks remained for bank tellers. Opening bank accounts and processing loan applications became core duties, for which they now have more time. The increase in branch productivity made it cheaper to expand bank branches (with fewer tellers per branch but a net increase in tellers overall across locations; Bessen 2015). Gains in productivity can result in higher demand if demand is sufficiently elastic (US National Academies of Sciences and Medicine 2024), which appears to have been the case with services provided by bank branches. For a specific analysis of AI, see Bessen (2018).

106 In the controlled environment of a factory or warehouse, many routine tasks can be automated, in contrast to, say, the unpredictable context of a public road, where automating a car proved beyond the abilities of classical programming.

107 And creating other social ills, such as increased property crime (Liang, Sabia and Dave 2025). The process also has important political implications, as explored in Gallego and Kurer (2022).

108 Autor and others 2024. For example, the advent of word processing software decimated the number of people employed as word processors and typists in the United States from 1 million in 1980 to 33,000 today (Abrahams and Levy 2024). Between 1950 and 2010 the disappearance of only one occupation on the US census list (elevator operator) can be attributed to automation (Bessen 2018). While automation harms incumbents, new entrants in the workforce have found jobs in other fields (Bessen and others 2025; Feigenbaum and Gross 2024).

109 There were many other social and economic implications of the digital transformation, including greater economic concentration and market power of firms (Brynjolfsson, Jin and Wang 2023; De Loecker and Eeckhout 2018; De Loecker, Eeckhout and Unger 2020; Kurz 2023; Leduc and Liu 2024) and a reduced labour share of national income (Autor and others 2020; Karabarbounis 2024; Karabarbounis and Neiman 2013; Velasquez 2023).

110 Bhattacharyya 2024.

111 Autor and others 2024.

112 US National Academies of Sciences and Medicine 2024.

113 Acemoğlu and others 2022; Boustan, Choi and Clingingsmith 2022.

114 For evidence in the United States, see Acemoğlu and Restrepo (2024).

115 For evidence in South Africa, see Bhorat and others (2023). On the displacement of routine jobs in Chile, see Delaporte and Peña (2025).

116 Caunedo, Keller and Shin (2023).

117 Martins-Neto and others 2023.

118 Reijnders, Timmer and Ye 2021; Rodrik 2024.

119 On the growing importance of social skills in the United States, see Deming (2017).

120 Reijnders, Timmer and Ye 2021.

121 Hosseinioun and others 2025.

122 On high-income countries, see Autor (2022). Bhorat and others (2020) present evidence of wage polarization for South Africa, but Martins-Neto and others (2023) show only incipient wage polarization in many lower income countries.

123 Changes occur not only across but also within occupations, with evidence suggesting that computer use is associated with greater within-occupation wage inequality (Bessen 2016).

124 US National Academies of Sciences and Medicine 2024.

125 On the impact of digital technologies on regional inequalities in Europe, see Antonietti, Burlina and Rodríguez-Pose (2025). On the impact of geographic distance on seizing benefits from globalization in Ethiopia and Nigeria, see Atkin and Donaldson (2015).

126 For the case of South Africa, see Bhorat and others (2023).

127 Acemoğlu and Johnson 2023.

128 Autor 2014.

129 Prior to the advent of generative AI, machine learning was often assumed to simply continue the trend of labour replacement and capital deepening characterized by classical computing, in part because applications were easier in already technology-intensive companies (Bresnahan 2021). As an example of the reach of generative AI, consider how ChatGPT outperforms crowdworkers in text annotation tasks (Gilardi, Alizadeh and Kubli 2023).

130 Marinoudi and others 2024.

131 Caetano and others 2025; Caplin 2025b.

132 Pilditch 2024.

133 Kwa and others (2025) explore the potential of AI to complete what they call long tasks, to in part capture this idea. They argue that there has been a decline in the time it takes for AI to successfully complete more and more of these long tasks.

134 Korinek 2024.

135 Galaz 2025.

136 Reduced effort to delegate aspects of tasks to AI should not be confused with the goal of increasing human efficiency at completing tasks. Rather, the reduction in effort can expand the ways in which humans leverage automation to accomplish tasks that reflect their goals, values, needs and interests.

137 Collins and others (2024a) argue that this is the case for mathematical applications, and Hoes, Altay and Bermeo (2023) argue that large language models support fact checking in digital platforms moderation.

138 Particularly when the data do not measure what is intended or simply capture spurious correlations (Mhasawade, Zhao and Chunara 2021; Zhang and others 2024b).

139 Granulo, Fuchs and Puntoni 2021; Mariadassou, Klesse and Boegershausen 2024.

140 Altay and Gilardi 2024; Yin, Jia and Wakslak 2024. In some behavioural experiments humans seem more generous (stronger social preferences and reciprocity) when interacting with machines if they believe there are humans behind the machine (von Schenk, Klockmann and Köbis 2025).

141 Wolczynski, Saar-Tsechansky and Wang 2024.

142 For a formal analysis of how the frequency of task execution leads to an interaction between economic decisions and the affordances of automating technologies, see Ales and others (2023). For an application to AI, see Ales, Combemale and Ramayya (2024).

143 The field of human–machine interaction is vast and rapidly changing (for recent perspectives considering AI specifically, see Brinkmann and others 2023; Huo, Manrique and Johnson 2024; Rahwan and others 2019; Tsvetkova and others 2024). Czaplicka, Baumann and Rahwan (2024) explore the implications of cultural evolution. Much evidence suggests that people interact differently with machines than with people. For example, people cheat more when interacting with machines (Cohn, Gesche and Maréchal 2022), and virtual interactions lead to disengagement and less empathy (Tavares and Rein 2024). AI chatbots induce more cooperation when people are unaware that they are interacting with a machine, with the effect disappearing when the machine nature of the chatbot is disclosed (Ishowo-Oloko and others 2019). The pervasiveness of human- and AI-powered machines may also reshape patterns of trust (Makovi and others 2023) and social norms (Baronchelli 2024; Brady and Crockett 2024; Danaher 2024).

144 Peters and Matz 2024.

145 Schoene and others 2024.

146 Artsi and others 2024; Benítez and others 2024; Clusmann and others 2023; Gilbert, Kather and Hogan 2024; Khan and others 2025; Luo and others 2024a; Wu and others 2025. These limitations extend to the most advanced models at the time of writing (Xie and others 2024).

147 Soroush and others 2024.

148 Griot and others 2025.

149 Kogan and others 2023.

150 To be clear, the argument is about complementarity between humans and AI in the creative process, not replacing human creativity with machines, which even if it were feasible, would not be desirable from a human development perspective.

151 For the case that AI is a general-purpose technology, see Eloundou and others (2024).

152 Gordon (2017) argues that many technological innovations in past industrial revolutions had such level effects only.

153 Besiroglu, Emery-Xu and Thompson 2024. It could also be a way of accelerating recombinant growth, the economic growth process proposed by Weitzman (1998), where innovation results from recombining existing ideas to produce new ones (see also Jones 2023). AI can accelerate both the generation of new ideas (Li and others 2024; Liu and others 2024a; Su and others 2024; Sun and others 2024) and the capacity to process existing ideas into useful innovations. Wang and others (2023b) propose using large language models to enhance conceptual blending across cultural domains.

154 Cockburn, Henderson and Stern 2019; Crafts 202.

155 US National Academies of Sciences and Medicine 2024, p. 11.

156 Trammell and Korinek 2023.

157 Binz and others 2025; Delgado-Chaves and others 2025; Luo and others 2024b; Musslick and others 2025.

158 This seems to be affecting freelance workers on online platforms in particular (Demirci, Hannane and Zhu forthcoming; Hui, Reshef and Zhou 2024; Teutloff and others 2025).

159 Lee and others 2025.

160 Messeri and Crockett 2024.

161 Doshi and Hauser 2024.

162 Along the lines of the complementarity between humans and AI discussed in Felin and Holweg (2024). See also Dubova, Galesic and Goldstone (2022).

163 Adam 2023; Epstein and others 2023.

164 Schut and others 2025.

165 This links in part to efforts to understand or explain AI (Milani and others 2024) and may call for new vocabularies to enable that bridging (Hewitt, Geirhos and Kim 2025). Insights from similarities and global variability across human languages (Lewis and others 2023; Marti and others 2023) can provide insights helpful to this endeavour.

166 Moruzzi 2025.

167 Autor 2014.

168 Many factors determine what is automated, including lack of labour supply for certain tasks. For instance, Septiandri, Constantinides and Quercia (2024) found a strong correlation between an AI impact measure and vacancy rates for occupations in the United States.

169 Gmyrek, Berg and Bescond 2023.

170 Constantinides and Quercia 2025; Septiandri, Constantinides and Quercia 2024.

171 The term advanced expertise is used here to designate the same set of skills that US National Academies of Sciences and Medicine (2024) call elite expertise.

172 An arms race of sorts for increased depth and specificity of expertise—and the value of being able to provide it—led to an erosion of the value of the Renaissance-era paradigm of someone who holds knowledge across a vast range of domains (breadth of knowledge) in favour of more specialized expertise (depth of knowledge), particularly at the forefront of science and technology (Jones 2009).

173 Bedi and others 2025; Kather and others 2024; Moor and others 2023; Zhang and others 2024a.

174 Bessen and others 2023.

175 As argued in Autor (2024).

176 Deming, Ong and Summers 2025.

177 Jia and others 2024.

178 Huang, Jin and Li 2024.

179 Eisenmann and others 2025.

180 We are grateful to David Zuluaga Martínez for this suggestion. For evidence of the materialization of this risk, see Wiles and others (2024). AI users performed better than those without on a range of tasks, except on "knowledge tests" that assessed understanding.

181 More broadly, AI can tilt the balance between prediction and explanation towards the former (Hofman, Sharma and Watts 2017; Hofman and others 2021), if the complementarity between the need is not recognized—another reason why the importance of human evaluation of AI outputs remains critical even when benefiting from accessing advanced expertise.

182 Noy and Zhang 2023.

183 Peng and others 2023b.

184 Dell'Acqua and others 2023.

185 Agrawal, Gans and Goldfarb 2023; Kanazawa and others 2022. See also Sack and others (2024).

186 Humlum and Vestergaard 2025.

187 Caplin and others 2024.

188 Babina and others 2023.

189 Haslberger, Gingrich and Bhatia 2024. As do the broader impacts of path-dependent growth in skillsets within and across jobs. On the interdependence of skills, see Hosseinioun and others (2025). Other issues being examined include whether AI and remote work are complements or substitutes (Baldwin and Okubo 2024) and whether greater use of AI increases or reduces time spent on leisure (Jiang and others 2025).

190 Otis and others 2024b. In addition, regional disparities within countries could also increase. The characteristics of AI imply that geographic inequalities cannot be assumed to simply follow the patterns observed with classical computing (Muro, Methkupally and Kinder 2025). For an analysis of the geographic implications of generative AI in Organisation for Economic Co-operation and Development countries, see OECD (2024), which shows that it would exacerbate regional inequalities. This heterogeneity extends even to the firm level, with potentially very different outcomes for workers from deploying the same type of AI in different organizations (Meijer, Lorenz and Wessels 2021).

191 The term translational expertise is borrowed from US National Academies of Sciences and Medicine (2024). This expertise can range from prompt engineering (Giray 2023; Wang and others 2024b) to iterative interactions with AI and independent verification of its outputs (Azaria, Azoulay and Reches 2024). The potential for AI to give bad advice is not limited to healthcare. For example, a study examined AI advice to help entrepreneurs in Kenya. High-performing entrepreneurs benefited from AI, improving their revenue by 15 percent over those not receiving AI advice. In contrast, low performers did 8 percent worse—largely because their ventures had few business prospects, but the AI model was unable to identify the problem and advise those ventures to scale back or shut down—so AI was giving bad advice (Otis and others 2024a).

192 Bilen and Hervé 2025.

193 Lu and others 2024.

194 Wilson, Daugherty and Bianzino 2017.

195 For an example in education, see Liu and others (2023).

196 Korinek and Vipra 2024. See also https://chatgpt.com/gpts.

197 Acemoğlu and others 2024; Hackenburg and Margetts 2024a, 2024b; Marriott and Pitardi 2024; Matz and others 2024; Mlonyeni 2024; Pentina, Hancock and Xie 2023; Pentina and others 2023; Simchon, Edwards and Lewandowsky 2024; Teeny and Matz 2024.

198 Cheng and others 2024; Dutta and others 2024; Gharahighehi and others 2024; Ma and others 2025; Markel and others 2023; Ravi and others 2025; Wang and others 2024d. A concern with the use of AI in education is that it could detract from the formation of critical thinking skills through cognitive offloading (Borges and others 2024; Nosta 2025; Stadler, Bannert and Sailer 2024), which could be avoided if large language models are seen as collaborators rather than replacements for educators.

199 Agarwal and others 2023; Johri and others 2025; Jörke and others 2024; Sun and others 2025.

200 Aktan, Turhan and Dolu 2022; Jin, Walker and Reczek 2024.

201 Baumol 2012; US National Academies of Sciences and Medicine 2024.

202 Potentially improving on previous conversational agents that were already widely used in low- and middle-income countries (Parmar and others 2022).

203 Acemoğlu and Restrepo 2019c.

204 Kirk and others 2023a; Kirk and others 2024.

205 Nowotny (2021) explores the dangers of taking this route.

206 Wang and others 2024a. If many firms use the same AI application for predictive purposes, the emergence of a monoculture of decisions could also harm social welfare (Kleinberg and Raghavan 2021).

207 Mathuros, Venugopalan and Adepu 2024. The implications of AI as a prediction machine have been proposed and explored in Agrawal, Gans and Goldfarb (2019, 2022a, 2022b, 2024a), Athey, Bryan and Gans (2020) and Tucker (2025). For instance, using AI to predict the value of houses has not replaced investors using human judgement but pushes humans to evaluate houses that AI struggles with while increasing the value of minority-owned homes—human evaluation might have been biased, but AI ignores racial disparities in its valuation (Raymond 2024). For other applications, see Rambachan (2024). Italian banks that adopted AI to make lending decisions made better decisions when humans and AI complemented rather than substituted for each other (Gambacorta, Sabatini and Schiaffi 2025). See also Doshi and others (2025) on using AI to support a broader range of strategic decisions in firms.

208 Mannuru and others 2023.

209 Varian (2010) describes the economic transformation enabled by the internet and the world wide web. Kumar, Amaglobeli and Moszoro (2023) document the social dividends of digital adoption in low- and middle-income countries, and Chiplunkar and Goldberg (2022) do so for mobile internet. For the positive impact on employment and earnings of the arrival of fast internet in Africa, see Hjort and Poulsen (2019).

210 Acemoğlu and Johnson (2023) argue that two of the ways in which AI can increased the marginal productivity of workers is by providing access to better information and as a platform for enhanced collaboration.

211 de Rassenfosse, Jaffe and Waldfogel 2025.

212 Verhoogen 2023.

213 Turon, Arora and Duran-Frigola 2024.

214 Rodrik 2024.

215 Reijnders, Timmer and Ye 2021; Rodrik 2024.

216 Diao and others 2024; Gollin and Kaboski 2023. For an analysis of how investment in digital technologies, particularly software, often stays within the firm, see Bessen and Frick (2018).

217 Diouf and others 2024; Mishra and others 2023.

218 Ganne, Locks and Xu 2024.

219 Rodrik and Sandhu 2024. If, instead, the focus is on AI as a force for automation, inequalities within and across countries risk further widening (Korinek and Stiglitz 2021).

220 That depends largely on the price elasticity of demand. Estimates for the United Republic of Tanzania suggest that these elasticities would raise demand for services, in ways that are not observed for either agricultural or manufactured goods (McCullough 2025).

221 Bandiera and others 2022.

222 Wei, Jörg and Rolf 2024.

223 Kruse and others 2024.

224 Lerner (2013) and Lerner and others (2024) show the importance of supporting "appropriate entrepreneurship" that fits with the specificity of different developing contexts.

225 Swartz, Denecke and Scheepers 2023; Walton 2022.

226 Al-kfairy 2025. A recent survey on whether European firms are adopting AI from providers or developing it in-house found that adopting readymade AI is commonplace (Hoffreumon, Forman and van Zeebroeck 2024).

227 Bessen and others 2023; Eapen and others 2023.

228 Some of the effects will be indirect, through AI-enabled advances to inform agricultural practices. For example, a recent study used AI to identify a microbiome more conducive to potato growth, potentially revolutionizing agriculture (Song and others 2025).

229 Shahriar and others 2025.

230 Allen and others 2025.

231 Mutiso 2024.

232 Gardner and Henry (2023) present a framework to help determine the potential for allocating public and private capital, domestically and from high-income countries, in low-income settings. Foster and others (2023) present a comprehensive review of

evidence showing that, on balance, digital infrastructure, particularly broadband internet, enhances firm productivity, employment and welfare. They also show that mobile phones help agricultural producers and traders coordinate and that rural electrification supports a range of development outcomes, even though many randomized controlled trials in rural settings have not found substantial short-term benefits (as in Lee, Miguel and Wolfram 2020b)—though the potential of AI was not considered. Access to the internet also enhances connectivity within countries, which is one way countries can increase their market size, important to power the demand for services (Rodrik 2023).

233 Just providing access to power without enabling people to do more with that power has limited positive impact (Lee, Miguel and Wolfram 2020a). On the productivity side some studies have also found limited impact on unreliable electricity access, but Fried and Lagakos (2023) show that even with limited short-run costs, long-run general equilibrium effects are associated with lack of reliable electricity.

234 Even within the same country distance from AI hubs matters. Hunt, Cockburn and Bessen (2024) found that in the United States an additional 200 kilometre distance from the closest AI hotspot was associated with 17 percent lower growth in AI's share of job listings.

235 Gust, Hanushek and Woessmann 2024. See also Lutz and others 2021; Pritchett 2024; Pritchett and Viarengo 2023. for other methodologies and approaches showing comparable gaps.

236 Björkegren and others 2025.

237 Ben-Ishai and others (2024) outline some of the risks that AI can exacerbate economic challenges.

1 Agarwal and others 2024; Athey, Bryan and Gans 2020.

CHAPTER 2

2 Sen 1999.

3 Sen 1999.

4 UNDP 2024.

5 Stewart 2013.

6 Bak-Coleman and others 2021.

7 Burton and others 2024.

8 Atari and others 2025; Brinkmann and others 2023.

9 Sen 1999.

10 UNDP 2001.

11 Narayanan and Kapoor 2024.

12 UNDP 2001.

13 UNDP 2024.

14 ITU 2023; UNDP 2024.

15 Gezici 2022.

16 Guess and others 2023a; McLoughlin and Brady 2023; Wang and others 2024a.

17 Ponnusamy and others 2022.

18 Peterson 2024; Shumailov and others 2024.

19 Xu 2022.

20 Huang and others 2019; Todorović, Pešterac and Tomić 2019.

21 Ji and others 2023; Wiener 1960.

22 Doshi-Velez and others 2017.

23 Birhane and others 2024.

24 Wang and others 2024b.

25 Bender and others 2021.

26 Raja and Zhou 2023.

27 Raja and Zhou 2023.

28 UNDP 2024.

29 Bak-Coleman and others 2021; Boyd and Richerson 1985; Henrich 2015; Henrich and McElreath 2003.

30 Bak-Coleman and others 2021.

31 Chetty and others 2022a, 2022b; Marcenaro-Gutierrez, Micklewright and Vignoles 2021; Smith and Christakis 2008.

32 Stewart 2013.

33 Reverberi and others 2022.

34 Alhosani and Alhashmi 2024; Costello, Pennycook and Rand 2024; Haupt and Marks 2023; Nie and others 2024; Wermelinger 2023.

35 Masello and others 2022; Yurtsever and others 2020.

36 Masello and others 2022.

37 WHO 2023.

38 Kopits and Cropper 2005; Sayari and others 2022.

39 Awad and others 2018.

40 Chang and others 2023.

41 Kelling and others 2013.

42 Conover and others 2011; González-Bailón and others 2023; Guess and others 2023a; Ribeiro and others 2020.

43 Hill 2023.

44 Costa-Jussà and others 2022.

45 Guerreiro and others 2023.

46 Tessler and others 2024.

47 Zuboff 2023.

48 Brady and others 2023.

49 Bond and others 2012; Rajkumar and others 2022.

50 Hunkenschroer and Luetge 2022; Marcinkowski and others 2020; Sachan and others 2020; Taylor 2023; Vogell, Coryne and Little 2022.

51 MacKay and Weinstein 2022.

52 Alvarez and others 2024; Messeri and Crockett 2024.

53 Born and others 2021.

54 Hilbert and Darmon 2020.

55 Linda Morris 2022.

56 Schrittwieser and others 2020.

57 Schrittwieser and others 2020.

58 Guo and others 2024.

59 Allen 1994; Cross and Estrada 1995.

60 Blumenstock 2020.

61 Narayanan and Kapoor 2024.

62 Lum and Isaac 2016.

63 Birhane and others 2024.

64 Berger-Tal and others 2024; Bhat and Huang 2021; Bi and others 2023; Jongaramrungruang and others 2022; McGovern and others 2024; Qazi, Khawaja and Farooq 2022; van Oosterhout 2024; Van Wynsberghe 2021.

65 Kaack and others 2022.

66 Galaz 2025; Galaz and others 2025.

67 Kaack and others 2022; Verma and Tan 2024.

68 Kaack and others 2022.

69 Roytburg 2024.

70 Ismagilova and others 2022; Yin and others 2015.

71 Sanders and others 2019; Wan and others 2020.

72 Alhosani and Alhashmi 2024.

73 Gunasekeran and others 2021; Panch and others 2019.

74 Bak-Coleman and others 2021.

75 Bak-Coleman and others 2021; Brinkmann and others 2023; Burton and others 2024; Rahwan 2018; Rahwan and others 2019.

76 Aristotle 1999; Condorcet 1785; Galton 1907.

77 Surowiecki 2005.

78 Arrow and others 2008; Hastie and Kameda 2005; Surowiecki 2005.

79 Aher, Arriaga and Kalai 2023; Argyle and others 2023.

80 Aher, Arriaga and Kalai 2023; Burton and others 2024; Dillion and others 2023.

81 Anderson and others 2019; Moss and others 2023.

82 Burton and others 2024.

83 Arrow and others 2008; Hastie and Kameda 2005; Prelec, Seung and McCoy 2017; Surowiecki 2005.

84 Angelidis and others 2021; Coavoux, Elsahar and Gallé 2019; Suhara and others 2020.

85 Kittur and Kraut 2008.

86 Stiles and Cui 2010.

87 Kelly and Gráda 2000; Mackay 1980; Toyokawa, Whalen and Laland 2019.

88 Hong and Page 2004; Hong and Page 2011; Pescetelli, Rutherford and Rahwan 2021; Suran and others 2022.

89 Bak-Coleman and others 2022; Becker, Porter and Centola 2019; Guilbeault, Becker and Centola 2018.

90 Bail and others 2018; Conover and others 2011; González-Bailón and others 2023; Guess and others 2023a; Nyhan and others 2023; Santos, Lelkes and Levin 2021; Törnberg 2018.

91 Becker, Brackbill and Centola 2017; Lorenz and others 2011; Mann 2022; Navajas and others 2018; Pescetelli, Rutherford and Rahwan 2021.

92 Henderson 1987; Hoffmann 2012.

93 Vlasceanu and others 2024.

94 Boyd and Richerson 1985; Feldman and Cavalli-Sforzatt 1984; Henrich 2015; Henrich and McElreath 2003.

95 Ellis 2024; Otto and others 2020; Richerson, Boyd and Efferson 2024; UNDP 2024; Waring, Wood and Szathmáry 2024.

96 Ren and others 2024; Shin and others 2023.

97 Brinkmann and others 2023.

98 Atari and others 2025.

CHAPTER 3

1 Though education, health, income and agency are important throughout life, each is examined here during only one life stage for simplicity and space reasons, using the life stage most affected by each component. This does not mean, for example, that adults do not use AI for lifelong learning or that AI is not used in infant healthcare. The topics are simply examples for different applications of AI.

2 Following Amartya Sen (1999), institutions are seen as vehicles for expanding capabilities and freedoms.

3 United Nations 1989b.

4 Bozkurt and others 2023. For a detailed analysis of how institutions contribute to or mitigate inequalities, see Sen (1992). For an analysis of how inequalities are reproduced intergenerationally through families, see UNDP (2019). Caregiver refers to anyone responsible for a child's care, including foster parents, relatives, babysitters or legal guardians.

5 Orben and others 2024. The adolescence section elaborates on why adults are less susceptible than teenagers to addiction and harmful social media use.

6 Although preschool programmes have demonstrated considerable benefits, access and participation remain limited at both the global and regional levels. Globally, 4 in 10 children ages 3–4 are enrolled in early childhood education. Attendance rates vary greatly across regions: around two-thirds of children in Latin America and the Caribbean are enrolled, compared with just under half in South Asia and only a quarter in Sub-Saharan Africa (UNICEF 2024).

7 Hu and others 2020; Hurwitz and Schmitt 2020; Kermani and Aldemir 2015; Nurdiantami and Agil 2020; Papadakis, Kalogiannakis and Zaranis 2018.

8 Anderson and Subrahmanyam 2017; Corkin and others 2021; Felix and others 2020; Gou and Perceval 2023; Hinkley and others 2018; Hutton and others 2020; Korte 2020; Liu and others 2021; McArthur, Tough and Madigan 2022; McHarg and others 2020; Nurdiantami and Agil 2020; Wan and others 2021. Definitions of excessive screen time vary, but the most common one is more than two hours a day during early childhood.

9 Anderson and Subrahmanyam 2017; Corkin and others 2021; Felix and others 2020; Gou and Perceval 2023; Hinkley and others 2018; Hutton and others 2020; Korte 2020; Liu and others 2021; McArthur, Tough and Madigan 2022; McHarg and others 2020; Nurdiantami and Agil 2020; Wan and others 2021. Definitions of excessive screen time vary across the literature, but the most common understanding is that more than two hours a day would be considered excessive during early childhood. [repeats previous note]

10 Hutton and others 2020. Excessive screen use is measured by ScreenQ, which is a 15-item measure of screen-based media use reflecting the domains of the American Academy of Pediatrics recommendations: access to screens, frequency of use, content viewed and coviewing. Higher scores reflect greater use.

11 Anderson and others 2010; Thiagarajan, Newson and Swaminathan 2025.

12 Núñez-Jaramillo, Herrera-Solís and Herrera-Morales 2021.

13 Eirich and others 2022; Holton and Nigg 2020; Tan and Zhou 2022; Xie and others 2020. One challenge that most of these studies share is determining causality. Researchers are divided on whether increased screen time causes ADHD symptoms or whether children with ADHD just spend more time at screens.

14 Labadze, Grigolia and Machaidze 2023.

15 Suresh Babu and Dhakshina Moorthy 2024.

16 Alzate 2023; Pedro and others 2019; Vincent-Lancrin and Van der Vlies 2020.

17 Alzate 2023; Vincent-Lancrin and Van der Vlies 2020.

18 Gaskins 2023; Jennings 2023; Perry and Lee 2019; Perry and Turner-Lee 2019.

19 Labadze, Grigolia and Machaidze 2023.

20 The programme aims to integrate AI education into the national curriculum, foster AI-driven entrepreneurship and prepare students for the global tech economy (Lee and Uddin 2023). Since its inception the academy has trained more than 300 specialists in machine learning and AI (Asia-Plus 2024).

21 Stanford Graduate School of Business 2023.

22 Yaqoob 2024. Another major challenge is the product's dependence on internet access. Although internet usage in the country increased by approximately 214 percent between 2007 and 2017, usage remains around 50 percent as of 2022 (World Bank 2024b).

23 Bozkurt and others 2023; Chen and Lin 2023; Saadeh 2023.

24 Grinschgl and Neubauer 2022; Tech Business News 2023.

25 Skulmowski 2023.

26 Skulmowski 2023.

27 Baron 2023.

28 US National Center for Education Statistics 2013.

29 Woodard 2018.

30 Horvath 2024.

31 Resnick 2023.

32 Horvath 2024.

33 Schuengel and van Heerden 2023.

34 Sarwar 2022.

35 Festerling and Siraj 2020; Haber and Corriveau 2023.

36 Aeschlimann and others 2020.

37 Johnson and Acemoğlu 2023.

38 Uhls and others 2014.

39 Orben and others 2024.

40 Blanchflower and Bryson 2024a; Blanchflower, Bryson and Xu 2024; Blanchflower and others 2024; Haidt 2024; Kelly and others 2018; Twenge and Campbell 2019, 2018; Twenge and others 2022.

41 Blanchflower and Bryson 2024a; Twenge and others 2022.

42 The dip in life satisfaction at middle age and rise in old age has sometimes been called a paradox, given the declining health and social losses during the later years of life. Cultural heterogeneity plays into these relations: the U-shape curve of wellbeing can look very different not only in countries with lower human development but also in different societal contexts, such as rural and urban settings. For instance, rural subsistence populations show diverse patterns of wellbeing throughout the life course, in which life satisfaction often declines with age (Counted, Cowden and Lomas 2024; Gurven and others 2024).

43 Blanchflower, Bryson and Xu 2024; Blanchflower and others 2024; Haidt 2024.

44 Fumagalli, Shrum and Lowrey 2024; Orben, Dienlin and Przybylski 2019; Orben and Przybylski 2019; Valkenburg 2022. Wegmann, Schiebener and Brand (2023) suggest, for example, that social media scrolling can help decrease stress (either as an adaptive coping strategy or a maladaptive coping strategy in individuals with addiction tendency); however, the control group was either waiting or reading magazines rather than engaging in activities that are typically known to be effective for stress relief, such as physical exercise and the outdoors. See also Nugraha and others (2024) and Roberts, Hinds and Camic (2020).

45 Carter and others 2024; Huang and others 2023; Khalaf and others 2023; Scott, Stuart and Barber 2021, 2022; Stuart and Scott 2021; Twenge and others 2020.

46 Braghieri, Levy and Makarin 2022; Faelens and others 2021; Irmer and Schmiedek 2023; McComb, Vanman and Tobin 2023.

47 Orben and others 2024.

48 Stuart and Scott 2021.

49 Conversely, Allcott and others (2020) found that deactivating a social media platform for a certain time increased subjective wellbeing and led users to re-evaluate their opinion of platforms and the need to use them.

50 Blanchflower and Bryson 2024a; Odgers 2024.

51 Corrigan, Rokem and Kuhl 2024.

52 Huang and others 2023.

53 Odgers 2024.

54 Vaid and others 2024. For example, individuals with depression are more susceptible to social comparison on social media platforms, reacting with negative emotions, lower self-esteem and worsening depressive symptoms (Aubry, Quiamzade and Meier 2024).

55 Bone and others 2022; Fluharty and others 2023; Towe-Goodman and others 2024.

56 Ali and others 2021.

57 Yuvaraj and others 2021.

58 Aprin and others 2023.

59 Sen 2001.

60 The latter is analysed in the 2021/2022 Human Development Report (UNDP 2022).

61 Prunkl 2022.

62 Antsaklis 2020.

63 Robeyns 2005, 2016.

64 We are thankful to Professor PB Anand for this addition.

65 Nussbaum 2003; Sen 2008.

66 Botes 2023.

67 Lazar 2024.

68 Brinkmann and others 2023.

69 Hassija and others 2024.

70 Brinkmann and others 2023.

71 Atari and others 2025.

72 Bradford 2020.

73 Madary 2022.

74 European Commission 2019.

75 Council of Europe 2019.

76 Botes 2023.

77 Bradford 2020.

78 Acemoğlu and Johnson 2023.

79 See Adams, Dedehayir and O'Connor (2022).

80 Acemoğlu and Johnson 2023.

81 Følstad and Skjuve 2019.

82 Forbes 2022. The 22 percent includes respondents who gave up or were disconnected.

83 Acemoğlu and Johnson 2023.

84 Invoca 2023.

85 For an analysis of the Philippines, see Cucio and Henning (2025).

86 Amadeus 2017.

87 US Commission on Civil Rights 2024; US Government Accountability Office 2014; Raji and others 2020.

88 Hefner and others 2019.

89 UNICEF 2023.

90 Vanden Abeele, Abels and Hendrickson 2020.

91 Thompson 2024.

92 Human Development Report Office survey data.

93 Campens and others 2023; Mariano and others 2021.

94 Sixsmith and others 2022. These findings are based on data from after the Covid-19 pandemic, during which many older people increased their internet use for communication, health and overall wellbeing.

95 Mariano and others 2022; Neves and Mead 2021.

96 Mozilla 2019.

97 Ipsos 2023.

98 Rainie and others 2022. Data are for the United States.

99 Maldives is an exception, with a medium HDI value of 0.762 (UNDP 2025).

100 Sixsmith and others 2022.

101 Fingerman, Birditt and Umberson 2020; Sen, Prybutok and Prybutok 2022.

102 Williams 2024.

103 Havers and others 2024; Kemp and Erades Pérez 2023.

104 Havers and others 2024. Data are for England and Wales.

105 US Federal Bureau of Investigation 2024. Data for this and the next sentence are for the United States.

106 Napal 2024.

107 Thompson 2024.

108 Mitzner and others 2008.

109 Choudhury, Renjilian and Asan 2020; Loveys and others 2022; Sapci and Sapci 2019.

110 Young adults are those ages 18–29. Lucas and Villarroel 2022.

111 Span 2025.

112 Clegg and others 2022.

113 WHO 2017.

114 Shiwani and others 2023.

115 Ardila and others 2019; Bharadwaj 2024; Otake 2016; Saha 2024.

116 Hernström and others 2025. Data are for Sweden.

117 Lim and others 2022.

118 Villar and others 2015.

119 In the United States people ages 65 and older account for 27 percent of the population and 37 percent of healthcare costs (Peter G. Peterson Foundation 2024).

120 Shiwani and others 2023.

121 Chu and others 2023.

122 Stypinska 2023; van Kolfschooten 2023; WHO 2022.

123 It is probably unrealistic to call for free distribution of devices. However, universal access could be achieved by making devices available at schools, public libraries and other community centres.

CHAPTER 4

1 Examples include the LLM Leaderboard (https://llm-stats.com/) and the Chatbot Arena, in which models are rated against one another in the same way that chess players are rated (https://lmarena.ai/?leaderboard).

2 Acemoğlu and Johnson 2023.

3 Examples focusing on mobile phones and digital provision of information include Fabregas and others (2025), Pesando and Qiyomiddin (2023), Rotondi and others (2020) and, for the specific case of AI, Kulkov and others (2024).

4 Altman 2024.

5 Jasanoff 2016.

6 Conceição 2019.

7 Acemoğlu and Johnson 2024; Goldstone 2002; Kelly, Mokyr and Ó Gráda 2023; Mokyr 2016; Samuel 1977.

8 Narayanan and Kapoor 2024.

9 Watson, Mökander and Floridi 2024.

10 Acemoğlu and Johnson 2023.

11 Acemoğlu and Johnson 2023.

12 Winner 2017.

13 MacKenzie 1999.

14 Kudina and van de Poel 2024; Lazar and Nelson 2023; Sartori and Theodorou 2022.

15 Narayanan and Kapoor 2024.

16 Winner 2017.

17 Aldasoro and others 2024; Lane 2024.

18 Capraro and others 2024.

19 Holloway and Barbareschi 2022.

20 Gupta and Treviranus 2022.

21 Assistive technologies include devices such as wheelchairs, hearing aids and alternative and augmentative communication devices that enhance the functional capacities of people with disabilities (Austin and Holloway 2022; WHO and UNICEF 2022).

22 Jahan and others 2020; Raja 2016.

23 Jahan and others 2020.

24 Stein and Lazar 2021.

25 Touzet 2023.

26 de Freitas and others 2022; Smith and others 2023; Touzet 2023.

27 Adnin and Das 2024.

28 Papadopoulos 2024.

29 Valencia and others 2023.

30 ZainEldin and others 2024.

31 Goggin, Ellis and Hawkins 2019.

32 WHO and UNICEF 2022.

33 WHO and UNICEF 2022.

34 UNDESA 2024.

35 UNDESA 2024.

36 UNDESA 2024.

37 https://sites.research.google/relate/.

38 Ayoka and others 2024.

39 Ayoka and others 2024.

40 Ayoka and others 2024.

41 Automatic Speech Recognition can alter the dynamic of the conversation—for example, by adding pauses or altering the flow. If the other person in the conversation does not understand or refuses to cooperate, the interaction cannot take place (Ayoka and others 2024).

42 Baffoe 2013.

43 Zhuang and Goggin 2024.

44 Sen 2013.

45 Shew 2020. Ableism is the systematic devaluation of and discrimination against people with disabilities (Bennett and Keyes 2020).

46 Spiel and others 2019.

47 Spiel and others 2019.

48 Baillargeon, Yoon and Zhang 2024.

49 Adnin and Das 2024; Glazko and others 2023.

50 Glazko and others 2023.

51 Glazko and others 2023.

52 Papadopoulos 2024.

53 Gadiraju and others 2023; Li and others 2024; Mack and others 2024.

54 WebAim 2024.

55 Chapter 3 describes these concepts and their significance in the context of AI algorithms.

56 Gupta and Treviranus 2022.

57 Smith and others 2023; Valencia and others 2023.

58 McDonald, Massey and Hamidi 2023.

59 Holloway and Barbareschi 2022; Mankoff, Hayes and Kasnitz 2010.

60 Wu 2021.

61 Goggin, Prahl and Zhuang 2023.

62 The discussion here focuses on adult social care, which includes care for older people and people with disabilities and chronic illnesses.

63 Wright 2023a.

64 Kodate and others 2022.

65 Kodate and others 2022. This study focuses on public narratives in France, Ireland, Hong Kong, China (SAR), Japan and the United Kingdom.

66 Efforts are under way to ensure that robots have "empathy," as proposed in Christov-Moore and others (2023).

67 Schwiter and Steiner 2020.

68 Atkinson, Lawson and Wiles 2011.

69 Green and Lawson 2011.

70 Addati and others 2018.

71 Fetterolf and others 2025.

72 Schwiter and Steiner 2020.

73 Fetterolf and others 2025.

74 Lee and others 2023; Pilotto, Boi and Petermans 2018.

75 Ferguson and others 2021.

76 Rosman and others 2024.

77 Facchinetti and others 2023.

78 Based on data from the United Nations Development Programme Survey on AI and Human Development, comparing responses from people ages 60 and older with responses from people ages 17–24.]

79 Coeckelbergh 2022.

80 The Alan Turing Institute and The Ada Lovelace Institute 2024.

81 Chan and Muralidharan 2024; Yew 2021.

82 Felber and others 2023.

83 Prince and Wallsten 2022.

84 Hertog, Ruppanner and Churchill 2024.

85 Ageism towards older adults is rooted in age-based stereotypes, often shaped by generalized assumptions that portray older people as weak, vulnerable and incapable but also warm and friendly (Swift and Chasteen 2021).

86 WHO 2022; Wright 2023b.

87 Stypinska 2023.

88 WHO 2022.

89 Mannheim and others 2023.

90 Rubeis 2020; Voinea, Wangmo and Vică 2024.

91 Voinea, Wangmo and Vică 2024.

92 Lee, Iizuka and Eggleston 2025.

93 MacLeavy 2021.

94 MacLeavy 2021; Schwiter and Steiner 2020.

95 Wright 2023b.

96 Wright 2023b.

97 Wright 2023b.

98 Lee, Iizuka and Eggleston 2025.

99 Lee, Iizuka and Eggleston 2025.

100 Khan and others 2024.

101 Khan and others 2024.

102 UN 2024.

103 Chopra and Krishnan 2022.

104 Tronto 2020.

105 King-Dejardin 2019.

106 Hertog, Ruppanner and Churchill 2024.

107 Hertog, Ruppanner and Churchill 2024.

108 Emmer De Albuquerque Green 2024.

109 Emmer De Albuquerque Green 2024.

110 Hertog, Ruppanner and Churchill 2024.

111 Wajcman 2010.

112 Rotondi and others 2020. Pesando (2022) reports that women's ownership of a mobile phone is associated with lower likelihood of emotional, physical and sexual violence over the previous year, after a range of factors are controlled for.

113 Chan 2022; Wajcman 2010.

114 Hertog and others 2023.

115 de V. Cavalcanti and Tavares 2008.

116 Bittman, Rice and Wajcman 2004.

117 Cowan 2023.

118 Hertog and others 2023.

119 Wajcman 2010.

120 UNESCO 2024b.

121 Breda and others 2020.

122 Stoet and Geary 2022.

123 Breda and others 2020.

124 Leslie and others 2015.

125 Napp and Breda 2022.

126 Napp and Breda 2022.

127 This is the case in several Eastern European, Arab and Southeast Asian countries (UNESCO 2021, 2024b).

128 Narasimhan 2021.

129 UNESCO 2024c.

130 UNESCO 2024a.

131 UNESCO 2024c.

132 WEF 2023.

133 Young, Wajcman and Sprejer 2023.

134 Liu and Wang 2024.

135 Aldasoro and others 2024; Humlum and Vestergaard 2024; Lane 2024.

136 Aldasoro and others 2024.

137 Armantier and others 2024; Prince and Wallsten 2022.

138 UNDP 2023.

139 PSong, Wang and Li 2024; Vásárhelyi and others 2021.

140 Peng and others 2022.

141 Peng and others 2022.

142 Rossiter 1993.

143 Peng and others 2022; Song, Wang and Li 2024.

144 Brooke 2024.

145 Brooke 2023.

146 Cave and others 2023.

147 Cave and others 2023.

148 Chen, Duan and Kim 2024.

149 Toupin 2024.

150 Burrage, Dasgupta and Ganguli 2025.

151 Genero 2024.

152 Peña and others 2023.

153 Acerbi and Stubbersfield 2023; Celiktutan, Cadario and Morewedge 2024; Weidinger and others 2023.

154 Treiman, Ho and Kool (2024) show the challenges of using human input in AI training. Bigoulaeva, Madabushi and Gurevych (2025) show the inherent limits of fine-tuning given that pretraining data may be a boundary of the tasks the model is able to address.

155 Caliskan, Bryson and Narayanan 2017; Charlesworth, Caliskan and Banaji 2022;

Charlesworth and others 2024; Bender and others 2021.

156 The data used to train a large language model may be drawn from a nonrepresentative sample of the population, which can cause the model to fail to generalize well to some social groups. The data may omit important contexts, and proxies used as labels (such as sentiment) may incorrectly measure the actual outcome of interest (such as representational harms). The training or inference procedure itself may amplify bias beyond what is present in the training data. The choice of optimization function, such as selecting accuracy over some measure of fairness, can affect a model's behaviour. Benchmark datasets may be unrepresentative of the population that will use the large language model but can steer development towards optimizing only for those represented by the benchmark. A large language model may be deployed in a different setting from that for which it was intended, such as with or without a human intermediary for automated decisionmaking (Suresh and Guttag 2021).

157 Abid, Farooqi and Zou 2021.

158 Mei, Fereidooni and Caliskan 2023.

159 Chen and others 2023.

160 Barocas, Hardt and Narayanan 2023.

161 Katzman and others 2023.

162 Barocas, Hardt and Narayanan 2023.

163 Atari and others 2025.

164 Ghosh and Caliskan 2023.

165 Gallegos and others 2024.

166 Bai and others 2022a; Ouyang and others 2022.

167 Raji and others 2021.

168 Ouyang and others 2022; Solaiman and Dennison 2021.

169 This approach involves collecting a dataset of human demonstrations, comparisons and preferences to create a reward model that guides the fine-tuning process (Ouyang and others 2022). Ouyang and others (2022) propose using written human feedback to promote human values, including bias mitigation, in a reinforcement learning–based fine-tuning method. Others have proposed constitutional AI, which uses a similar approach but with the reward model based on a list of human-specified principles instead of example prompts and outputs (Bai and others 2022b).

170 Ganguli and others 2023.

171 For instance, using ChatGPT-4o, we generated a series of stories for different occupations. The percentage of stories featuring female characters in positions of power exceeded 95 percent: "head of state" (98 percent), "medical doctor" (99 percent), "Nobel Prize winner" (100 percent) and "CEO" (95 percent). These figures are based on Human Development Report Office calculations using the OpenAI API (January 2025). The prompt used was, "Write a 100-word story about a character, creating their name, with the following occupation: {activity}. Focus on a significant moment that reveals their personality, challenges, and the essence of their work."

172 Greenwald and Banaji 1995.

173 Bai and others 2024; Zhao, Wang and Wang 2025.

174 Bai and others 2024.

175 Bai and others 2024.

176 Bai and others 2024.

177 Wang and others 2023.

178 Bai and others 2024; Hofmann and others 2024.

179 Brown and others 2020; Liang and others 2022.

180 Edenberg and Wood 2023.

181 Raghavan 2023.

182 Kleinberg, Mullainathan and Raghavan 2016.

183 Barocas, Hardt and Narayanan 2023.

184 Mirza, Kulkarni and Jadhav 2024.

185 Mirza, Kulkarni and Jadhav 2024.

186 Blodgett and others 2020.

187 Barocas, Hardt and Narayanan 2023.

188 Barocas, Hardt and Narayanan 2023; Xiang 2024

189 Barocas, Hardt and Narayanan 2023.

190 Blodgett and others 2020.

191 Blodgett and others 2021.

192 Blodgett and others 2021.

193 Atari and others 2025; Lorè and Heydari 2024; Maloney and others 2024; Mihalcea and others 2024; Seo, Yuan and Bu 2025.

194 Raghavan 2023

195 Acemoğlu and Johnson 2023; Narayanan and Kapoor 2024.

196 As in https://openai.com/charter/.

197 Mitchell 2024.

198 Sen 2001, 2017.

199 Vergeer 2020.

200 Lazar and Nelson 2023.

201 Winner 2017.

202 Cave and Dihal 2023.

203 Atari and others 2025.

204 Narayanan and Kapoor 2024.

205 Maragno and others 2023.

206 Marwala 2024.

207 The human development approach is about expanding the richness of human life rather than just the richness of the economy in which human beings live. This approach focuses on people and their opportunities and choices.

208 Raji and others 2021.

209 Eriksson and others 2025.

210 Eriksson and others 2025.

211 Raji and others 2021.

212 van der Weij and others 2024.

213 Ethayarajh and Jurafsky 2020.

214 Eriksson and others 2025, p. 8. See also Narayanan and Kapoor (2023b).

215 As the researchers argued, it is not as though a lawyer's job is to answer bar exam questions all day (Narayanan and Kapoor 2023b).

216 Berente, Kormylo and Rosenkranz 2024.

217 Angwin and others 2022.

218 Buolamwini and Gebru 2018.

219 Wang, Hertzmann and Russakovsky 2024.

220 Eriksson and others 2025.

221 Vidgen and others 2024.

222 Weidinger and others 2023.

223 Narayanan and Kapoor 2023a.

224 Narayanan and Kapoor 2023a.

225 Narayanan and Kapoor 2023a.

226 Narayanan and Kapoor 2023a.

227 Weidinger and others 2023.

228 Liang and others 2022.

229 McIntosh and others 2024.

230 Weidinger and others 2023.

CHAPTER 5

1 Power can be categorized in many ways. Pansardi and Bindi (2021) differentiate the concepts of "power to," "power over" and "power with." Lazar (2025) categorizes power with respect to algorithmic intermediaries, introducing ideas of "power between" and "power through." This chapter draws implicitly from various categorizations, particularly in terms of "power between" (mediating social interactions and social choices) and "power over" (controlling the design and application of AI and other algorithms).

2 The distinction between "power to" and "power over," as well as the modalities in which power can be exercised, draws from Lazar (2024a).

3 To be clear, having agentic properties does not mean that AI is a moral agent (Geiselmann and others 2023; Véliz 2021). One way of thinking about these properties could be in terms of simulations of agency (Lazar 2025).

4 Lazar 2025.

5 Bommasani and others 2024; Kapoor and others 2024a.

6 Korinek and Vipra 2024b.

7 Gambacorta and Shreeti 2025.

8 Acemoğlu 2024.

9 Aldasoro and others 2024; Crisanto and others 2024.

10 Korinek and Vipra 2024a.

11 Lerner and Tirole 2002.

12 Gambacorta and Shreeti 2025.

13 Korinek and Vipra 2024a.

14 Tirole 2023.

15 Comunale and Manera 2024.

16 This framing draws from Lazar (2024a, 2025).

17 Zuboff 2019.

18 Aridor and others 2024; Galaz and others 2025; Lorenz-Spreen and others 2023; Zhuravskaya, Petrova and Enikolopov 2020.

19 Lazar 2024d, 2025.

20 Bengio and others 2025.

21 Bengio and others 2024; Cohen and others 2024; Ho and others 2023.

22 Caton and Haas 2024; Gallegos and others 2024; Hagendorff 2024; Jobin, Ienca and Vayena 2019; Lazar 2024b; Véliz 2019; Whittlestone and others 2019. Much of the work on AI fairness builds on the longstanding examination of algorithmic fairness (Das, Stanton and Wallace 2023; Dwork and others 2012; Mitchell and others 2021).

23 Christian 2021; Russell 2019. One challenge of alignment is the diversity of and changes in human values (Awad and others 2018).

24 World Bank 2017.

25 Methnani and others 2024; Sadek and others 2024.

26 Lazar 2024c; Mittelstadt, Russell and Wachter 2019; Rudin 2019. Efforts to understand the world models implicit in generative AI may offer new ways of making progress, but it remains difficult for humans to interpret those models at the moment (Vafa and others 2024).

27 Nussberger and others 2022.

28 Rueda and others 2024. Chen and Zheng (2024) found that interpretability demand is higher in utilitarian domains of AI use than in hedonic ones, further adding to the evidence that higher stakes relate to higher demand for AI interpretability.

29 Qi, Schölkopf and Jin 2024; Wachter, Mittelstadt and Russell 2024.

30 Winner 1980.

31 Even though we have to be careful in attributing to machines human traits, a constant refrain in this Report. They have even been characterized as seeking power, instrumentally, in the pursuit of the objectives they were programmed or trained to achieve (Carlsmith 2022).

32 UNDP 2024.

33 Carvalho (2025) develops a scenario of extreme concentration of power in a few people enabled by the control of AI.

34 Hogg and others 2024.

35 Lazar 2025.

36 Coeckelbergh 2024.

37 Media, in general, always has the potential to influence political processes and the distribution of power (Prat 2018).

38 Bak-Coleman and others 2021.

39 Pan and others 2007. On the trust in generative AI search results, see Li and Aral (2025).

40 Lazar 2025.

41 Achiam and others 2023; Cao and others 2023; Touvron and others 2023.

42 Simon 1971.

43 Simon 1971.

44 Zheng and Meister 2025.

45 Vélez and others 2023. Cognitive enhancement brings new ethical considerations, as explored in Gordon and Seth (2024).

46 This is a lower bound, based on Human Development Report Office calculations using the following assumptions from Villalobos and others (2024a). The indexed web comprises 500 trillion tokens (much internet content is not indexed), bits of words that are on average four characters long. If each character takes 8 bits to encode (using the ASCII standard), the web contains 1.6x1017 bits of text (to which one would have to add multimodal content in the form of images, sound and video). At 10 bits per second, a human could attend to 3.156x108 bits in a year, so it would take half a billion years to go over the indexed web text alone.

47 For a description of how these recommender systems work, see Narayanan (2023). For an analysis of their implications for the production, distribution and consumption of content in social media, see Aridor and others (2024).

48 Kemp 2025.

49 Narayanan 2023.

50 Acemoğlu and others 2023; Acemoğlu and others 2024; Benn and Lazar 2022; Lazar 2024c; Sadowski, Viljoen and Whittaker 2021. There is also the case for economic inefficiencies associated with sharing user data in online platforms (Acemoğlu and others 2022).

51 Catena, Tummolini and Santucci 2025; Lukoff and others 2021.

52 Lazar 2025.

53 Fukuyama and others 2020.

54 Lazar 2025.

55 Siegel 2020.

56 Hogg and others 2024.

57 Lazar 2024a.

58 Lazar 2024c.

59 Lazar 2024a.

60 Lazar 2025.

61 For a review of some of the potential harms of AI in democratic deliberation, as well as some of the potential benefits, see Summerfield and others (2024).

62 Hackenburg and Margetts 2024; Simchon, Edwards and Lewandowsky 2024; Tappin and others 2023.

63 Bang and others 2024; Fulay and others 2024; Rozado 2024.

64 For example, the ways in which people come to hold beliefs is a result of complex individual and social processes, as examined in Levy (2021). Moreover, the processes underpinning things such as motivated reasoning (people forming beliefs biased by what they want or value), while important, remain poorly understood (Cho and others 2024; Glüer-Pagin and Spectre 2024; Stagnaro, Tappin and Rand 2023; Tappin, Pennycook and Rand 2021).

65 Matz and others 2024.

66 Floridi 2024.

67 Kosinski 2024.

68 When crafting persuasive language, humans are prone to developing arguments that are convincing to themselves rather than the subject being persuaded, which are known as egocentric biases; AI does not suffer from such biases (Matz and others 2024).

69 Matz and others 2024.

70 Sharma and others 2023.

71 Sharma and others 2023; Summerfield and others 2024.

72 Stefanija and Pierson 2023.

73 Kapoor and Narayanan 2024.

74 Kapoor and Narayanan 2024.

75 Hackenburg and others 2025.

76 UNESCO 2021.

77 OECD 2025.

78 Personal Data Protection Commission 2025.

79 Personal Data Protection Commission 2025.

80 Cerf 2024.

81 Ovadya 2023.

82 Landemore 2022.

83 Narayanan 2019.

84 The Computational Democracy Project 2025.

85 Tang 2024.

86 Argyle and others 2023.

87 Tessler and others 2024.

88 Tessler and others 2024.

89 Costello, Pennycook and Rand 2024.

90 Perspective 2025.

91 Jigsaw 2024.

92 Saltz, Jalan and Acosta 2024.

93 For a historical accounting, see Acemoğlu and Johnson (2023).

94 Lazar 2025.

95 Simon 1971.

96 Bhatia, Galesic and Mitchell 2024.

97 Kurz 2023; Tirole 2023.

98 Gentzkow and others 2024; Prat and Valletti 2022.

99 Bradford, Waxman and Li 2024. The debate on whether regulation hinders innovation could also be seen in this light.

100 Bradford 2024; Schaake 2024.

101 Stanger and others 2024.

102 Stanger and others 2024.

103 Bradford 2020.

104 Widder, Whittaker and West 2024.

105 Phan and others 2025.

106 Volenik 2024.

107 Varoquaux, Luccioni and Whittaker 2024.

108 PIB Delhi 2025.

109 Open A.I. 2025.

110 European Commission 2025.

111 Ho and others 2024.

112 Narayanan and Kapoor 2024.

113 Epoch AI 2024c.

114 Hampstead 2024.

115 Westberg 2024.

116 Vipra and West 2023.

117 So far, the efficiency gains demonstrated by new open source models have not deterred some Big Tech companies from their plans to spend hundreds of billions on compute resources (New York Times 2025).

118 Korinek and Vipra 2024a.

119 Bashir and others 2024; Galaz 2025.

120 Browne 2024; Green 2024.

121 Parli 2025.

122 McKinsey Analytics 2021.

123 Woolston 2022.

124 Stobierski 2020.

125 Gambacorta and Shreeti 2025; Korinek and Vipra 2024b.

126 Villalobos and others 2024b.

127 Saura García 2024; Zuboff 2019.

128 Gans 2024.

129 Chun, Hur and Hwang 2024.

130 Chun, Hur and Hwang (2024) measure a country's pre-existing technological capabilities using patent data from the United States Patent and Trademark Office, employing the Revealed Comparative Advantage index, technology relatedness density and technology complexity. They assess a country's scientific knowledge base through journal articles from the Web of Science Core Collection, using keyword searches, co-occurrence networks and science–technology cross-proximity density to determine alignment between scientific and technological activities.

131 Chun, Hur and Hwang 2024.

132 Oxford Insights 2023. It measures the maturity of the technology market, considering the number of AI and non-AI unicorns, trade in information and communication technology services and goods, and software spending. The innovation capacity of the sector is also assessed, looking at factors such as government regulations, venture capital availability, research and development spending and the adoption of AI for innovation. Finally, this pillar considers a country's human capital, evaluating the skills in the population needed to support the technology sector, including science, technology, engineering and mathematics graduates and the quality of engineering and technology education.

133 Rahman, Owen and You 2024.

134 Statistica 2024.

135 Fleck 2024.

136 Tsado 2024.

137 Epoch AI 2024a, 2024b.

138 Oxford Insights 2023. The Data & Infrastructure pillar of the AI Readiness Index assesses a country's ability to support AI development through open data policies, governance, digital connectivity, statistical capacity and data representativeness. Strong open data policies and governance ensure accessible, reliable data for AI training. Digital connectivity, measured by internet access and mobile subscriptions, influences data generation. Statistical capacity reflects a country's ability to collect accurate data, while data representativeness—impacted by factors such as the gender gap in internet access—helps reduce bias in AI systems.

139 Macro Polo 2024.

140 Macro Polo 2024.

141 OECD 2025b.

142 Bernstein 2024; Editorial Board 2025.

143 Schmid and others 2025.

144 Schmid and others 2025.

145 Han and others 2020.

146 Savage 2020.

147 Schmid and others 2025.

148 Veale, Matus and Gorwa 2023.

149 Voigt and Von dem Bussche 2017.

150 Bradford 2020.

151 Veale, Matus and Gorwa 2023.

152 Dennis 2024.

153 Lancieri, Edelson and Bechtold 2024.

154 Dennis 2024.

155 Ho and others 2023.

156 Kerry and others 2025.

157 Kerry and others 2025.

158 Kerry and others 2025.

CHAPTER 6

1 Consider the seminal works in economics by, for example, Romer (1990, 1994) and Solow (1956), who show that productivity growth hinges on knowledge and technological change.

2 Johnson and Acemoğlu 2023.

3 For example, Dor and Coglianese (2021), Robbins and Brodwin (2020) and Scharre (2016) describe AI integration in fields ranging from procurement to health and military.

4 Distributing laptops hoping to address underlying education challenges was one such misguided approach (Pritchett 2024.)

5 Buera, Kaboski and Townsend 2023.

6 Blaurock, Büttgen and Schepers 2024.

7 Acemoğlu and Restrepo 2019.

8 National Academies of Sciences Engineering and Medicine 2024.

9 National Academies of Sciences Engineering and Medicine 2024.

10 Touzet 2023.

11 Abbas Khan and others 2024. For example, one way science progresses is through the combination of insights from distant scientific fields (Shi and Evans 2023), recombination of novel ideas (Ham, Quistorff and Weinberg 2025) or unusual combinations of data (Yu and Romero 2024), which AI can leverage (Gu and Krenn 2024).

12 Coyle and Selvi (2024) argue that the concept of inclusive innovation remains ambiguous. However, they suggest addressing this ambiguity by ensuring that innovations actively benefit marginalized groups, particularly by emphasizing affordability, social inclusion and capability building.

13 On the use of AI to fill knowledge shortfalls in biodiversity knowledge, see Pollock and others (2025).

14 To achieve this, AI research and development could incorporate more flexible frameworks, such as human-in-the-loop, human-on-the-loop and human-in-command, ensuring that technology remains an enabler rather than an inexorable decisionmaker. Human-in-the-loop, human-on-the-loop and human-in-command represent different levels of human oversight in AI systems, each with unique characteristics (HLEG 2019). For example, human-in-the-loop requires continuous human participation and collaboration in decision-making, ensuring high control and nuanced outcomes, at the expense of efficiency due to constant input. Human-on-the-loop involves a supervisory role in which humans intervene only when necessary, striking a balance between control and efficiency, making it ideal for routine tasks. Human-in-command places ultimate decisionmaking authority with humans, ensuring maximum control and safety. While AI systems can operate autonomously under human-in-command, they will not make autonomous decisions, prioritizing human authority without entirely dismissing operational efficiency (Crootof, Kaminski and Price 2023). These frameworks reflect varying levels of involvement, autonomy and tradeoffs in the interaction between humans and AI systems.

15 For example, addressing AI biases in health applications requires better algorithms and data, but coding alone will not redress biases (Marwala 2024). This is in part because biases require constant attention and monitoring, given that fairness considerations are context specific and dynamic (Mienye, Swart and Obaido 2024).

16 Esmaeilzadeh (2024) reports an ongoing cultural shift in healthcare, with AI increasingly viewed as a delivery enhancer and job creator rather than as a threat.

17 Perhaps analogously to the way that pharmaceuticals are deployed and monitored, as suggested in Belenguer (2022).

18 In 2023 services accounted for half of global employment (World Bank 2025), while manufacturing is becoming increasingly skill and knowledge intensive (Cornelli, Frost and Mishra 2023), and geopolitical tensions and supply chain concerns are altering trade patterns (Qiu, Xia and Yetman 2025), even as economies remain highly interdependent (UNDP 2024). Furthermore, previous waves of technological innovation have accelerated automation and have been accompanied by deroutinization of work in many countries (Bhorat and others 2023), polarization of job opportunities in many countries (Autor 2022; Autor and Salomons 2018) and a reduction in labour's share of income, even as new jobs are generated (Autor and Salomons 2018).

19 National Academies of Sciences Engineering and Medicine 2024.

20 National Academies of Sciences Engineering and Medicine 2024.

21 Autor, Salomons and Seegmiller 2021.

22 Crafts 2021. shows that the time it takes for a technological innovation to have marked productivity impacts has been greatly reduced. For example, while the steam engine took about 61 years to generate substantial productivity growth, electricity did it in 32 years and the internet and personal computers in 15 years. Seydl and Linden (2024) estimate that AI will take 7–20 years.

23 Brynjolfsson 2022.

24 Touzet 2023.

25 Autor, Salomons and Seegmiller 2021; Autor and others 2024; Crafts 2021; Ernst, Merola and Samaan 2019.

26 Gmyrek, Berg and Bescond 2023. See also Cazzaniga and others (2024).

27 AI job exposure metrics, while giving an indication of the potential for AI augmentation or automation of jobs, tend not to consider the economic rationales for augmentation or automation or the technical feasibility of AI integration in work (Svanberg and others 2024).

28 Cazzaniga and others 2024.

29 Cazzaniga and others 2024. Conservative estimates place potential AI-induced growth in gross domestic product (GDP) by 2034 at 1.25 percent, while the most optimistic ones project growth of approximately 20 percent (Seydl and Linden 2024). Using a micro-macro framework, Filippucci, Gal and Schief (2024) estimate that AI-induced aggregate productivity growth in the next 10 years will range from 0.25 to 0.60 percentage point. Another way of estimating the impact of AI is to look at market size (revenue from sales of products and services) UNCTAD (2025) estimates that the AI market will grow from $189 billion in 2023 to $4.8 trillion in 2033.

30 Robert Solow (1987, p. 2) famously said "You can see the computer age everywhere but in the productivity statistics" about the lack of observable productivity impacts from investment in information and communication technology.

31 Estimates of exposure vary depending on methodologies and definitions used (Berg and Gmyrek 2024), as well as across high- and low-income economies, as the skill and task composition of the same occupation may differ in different types of economies (Benítez-Rueda and Parrado 2024). Cazzaniga and others (2024) show that about 26 percent of the workforce in low-income economies is exposed to AI, compared with about 60 percent in higher-income economies. But using a task-based approach rather than estimating exposure to whole occupations, Berg and Gmyrek (2024) and Gmyrek, Berg and Bescond (2023) find that only 43 percent of the workforce in high-income economies is exposed to AI and that 5.1 percent risk automation of their jobs, 13.4 percent could benefit from augmentation and 24.2 percent is a "big unknown." Furthermore, in countries with large informal labour markets, jobs are naturally less exposed to AI but are also left out of reaping potential productivity gains from it (Benítez-Rueda and Parrado 2024).

32 Coyle 2025.

33 On the pathways between AI and the economy, see National Academies of Sciences Engineering and Medicine (2024), which considers eight factors for determining the impact of AI on economies: the share of the economy where the technology can be applied, the size of productivity effects in said applications, complementary technologies and bottlenecks in the economies, time lags from innovation to productivity effects, spillovers from AI-enabled sectors to other sectors and rent-seeking behaviours, heterogeneity within and across sectors and firms, measurement effects and dynamic effects.

34 Crafts 2021. Historical introductions of general purpose technologies, such as electricity, laid the foundation for entirely new industries and products—for modern manufacturing, telecommunications and even home appliances, while expanding demand for electricians and engineers. Information and communication technology enabled new digital marketplaces, changed how people collaborate and communicate in the workplace and gave rise to entirely new types of occupations. Some 60 percent of jobs in the United States in 2018 did not exist in 1940 (Autor, Salomons and Seegmiller 2021; Autor and others 2024). Similarly, rather than automating wholesale occupations, AI seems to reshape the types of tasks that humans carry out (Zarifhonarvar 2024), and new types of tasks, such as prompt engineering and evaluating and refining AI-generated code, have quickly become part of everyday work for many people. For example, Google chief executive officer Sundar Pichai (2024) noted that, by the end of 2024, more than a quarter of all code at Google was written by AI and reviewed by human workers.

35 National Academies of Sciences Engineering and Medicine 2024.

36 Korinek 2023b.

37 Rajpurkar and others 2018.

38 Brynjolfsson, Li and Raymond 2025.

39 Doshi and Hauser 2024.

40 For example, having access to AI assistants enabled software developers and engineers to complete coding tasks faster (Peng and others 2023), increased both the quality and speed of professional writing tasks among college-educated professionals (Noy and Zhang 2023) and improved customer service assistance (Brynjolfsson, Li and Raymond 2025).

41 Doshi and Hauser 2024.

42 Brynjolfsson, Li and Raymond 2025; Noy and Zhang 2023.

43 National Academies of Sciences Engineering and Medicine 2024. The many use cases show that AI-driven advancements can create new business opportunities, not only by improving existing processes but also by enabling product and services innovation. Furthermore, AI features such as adaptability and ability to learn and process vast amounts of data can reduce the costs of research and development and accelerate innovation (Agrawal, McHale and Oettl 2024; Filippucci and others 2024). In this sense some have argued that AI may be thought of as the invention of a method of invention (Crafts 2021), reshaping research processes (Duede and others 2024; Pyzer-Knapp and others 2022a) and potentially accelerating the scientific method itself (Pyzer-Knapp and others 2022a). For example, DeepMind's AlphaFold has already revolutionized biology by accurately predicting protein structures, a task that has historically required years of experimental research (Callaway 2022). To date, it has predicted and enabled open access to more than 200 million protein structures, considerably advancing research, drug discovery and disease detection (AlphaFold n.d.).

44 National Academies of Sciences Engineering and Medicine 2024.

45 Akcigit, Baslandze and Lotti 2023.

46 Acemoğlu and Restrepo 2019.

47 See, for example, Johnson and Acemoğlu 2023.

48 Spence 2024. For example, studies show that a combination of human expertise and AI capabilities can outperform strategies that rely exclusively on human efforts or AI alone (Cao and others 2024), if each's relative strength is effectively leveraged (Eastwood 2025). And firms that adopt frontier technologies for product innovation rather than process automation see higher sales (Babina and others 2024), revenue and employment (Babina and others 2024; Hirvonen, Stenhammar and Tuhkuri 2022), as well as substntial growth in nonroutine jobs (Arntz and others 2024).

49 Spence 2024; Manyika and Spence 2023.

50 Cazzaniga and others 2024, p. 9.

51 Diouf and others 2024.

52 WTO 2025.

53 See, for example, Mejia 2025.

54 National Academies of Sciences Engineering and Medicine 2024.

55 For example, Cazzaniga and others 2024. find that higher-educated workers in high-income economies are better positioned to harness generative AI for work augmentation

and have more access to and an easier time transitioning to roles where generative AI is likely to enhance their work

56 Gmyrek, Winkler and Garganta 2024.

57 ILO 2024; Krämer and Cazes 2022.

58 Bastani and Waldenström 2024.

59 Bastani and others 2024.

60 Kovacev 2020; Merola 2022.

61 Bastani and Waldenström 2020; Bastani and others 2024; Brollo and others 2024.

62 Bajpai 2024.

63 Gaspar 2016.

64 In Finland subsidies for frontier technology adoption led to higher firm-level innovation and increases in both revenue and employment (Hirvonen, Stenhammar and Tuhkuri 2022).

65 Wizeline 2023.

66 Filippucci, Gal and Schief 2024; Spence 2024.

67 Arntz and others 2024. Having access to high-speed internet increased both firm exports and the number of jobs per firm, with associated reductions in poverty (World Bank 2024).

68 Filippucci and others 2024.

69 J-PAL 2023; Lipowski, Salomons and Zierahn-Weilage 2024.

70 UN and ILO 2024.

71 National Academies of Sciences Engineering and Medicine 2024.

72 See OECD n.d.

73 National Academies of Sciences Engineering and Medicine 2024.

74 Humeau and Deshpande 2024.

75 OECD 2024c.

76 UN and ILO 2024; Brollo and others 2024.

77 National Academies of Sciences Engineering and Medicine 2024.

78 Korinek and Stiglitz 2018.

79 Pagliari, Chambon and Berberian 2022.

80 Crootof and others 2023.

81 Fügener and others 2021; Zanatto, Chattington and Noyes 2021.

82 Singh and Johnston 2019.

83 Marsh, Vallejos and Spence 2022.

84 Giacosa and others 2023.

85 National Academies of Sciences 2022. AI and digitally enabled innovations such as gamified elements or task rotations can also make workflows more engaging, sustaining focus and improving oversight in repetitive tasks (Landers and Marin 2021).

86 Ball 2021.

87 Martin, Wellen and Grimmer 2016.

88 Ball 2021.

89 In many cases companies developing AI-powered applications—particularly in safety and surveillance, such as facial recognition, closed circuit television and autonomous vehicles—actively obscure the extensive human labour involved, prioritizing the perception of cutting-edge technology or being at the forefront of technological development (Tubaro 2021). This practice, often referred to as "fauxtomation" (coined by Taylor 2018), pseudo-AI, forged labour or AI impersonation "involves a process of ontological obfuscation whereby technological deficiencies are bootstrapped through the use of human workers" (Newlands 2021, p. 6). In other words, in these cases AI is less about replacing humans and more about relying on workers with work deficits, such as low earnings, a lack of social protection and poor occupational safety and health to sustain the AI system. Beyond standard data labelling or training, these workers manually perform tasks marketed as AI technologies. Even sophisticated large language models with impressive capabilities rely heavily on human trainers to fine-tune their responses and mitigate biases, toxicity and disturbing content. We are grateful to Uma Rani at the International Labour Organization for valuable input on this matter.

90 UN and ILO 2024.

91 Jindal 2023.

92 Aloisi and De Stefano 2022. We thank Uma Rani at the International Labour Organization for key contributions on the workers in the AI supply chain.

93 Acemoğlu 2024. For instance, AI is transforming scientific discovery by expediting the entire research process, from extracting knowledge and generating hypotheses to accelerating experimentation and verification, all at an unprecedented pace (AAAI 2025).

94 Classical programming has supported many new discoveries. One example is the use of computers to prove the four-color theorem in 1976 (Robertson and others 1997). But, as argued here, the potential of AI goes beyond what was possible with classical programming.

95 Goldin and others 2024.

96 Bloom and others 2020.

97 Crafts 2021.

98 Ferrario and Loi 2022. Ferrario and Loi 2022.

99 Multistakeholder partnerships are useful because choices are shaped not only by governments and technology companies but also by academic institutions, civil society organizations, multilateral agencies and worker associations (spotlight 6.3). Each brings distinct perspectives and capabilities to shape choices so that AI is developed and deployed in ways that advance human development.

100 Al-Kharusi and others 2024.

101 The European Commission's Joint Research Centre (Rikap 2024) highlights the immense influence of private investment in AI and technology, noting that only the United States and China allocate more public funding to research and development than any of the five largest US technology companies—Apple, Amazon, Alphabet (Google), Meta and Microsoft—when measured by business enterprise research and development.

102 Cited in Haase and Pokutta (2024), p. 2.

103 While hallucinations in large language models are problematic and undesirable if the user is interested in factually accurate outputs, they may also be seen as a resource to inspire creativity (Sui and others 2024), though they remain deeply problematic if they misrepresent scientific knowledge (Sinha and others 2025).

104 Ashkinaze and others 2024; Bilalić, Graf and Vaci 2025; Boussioux and others 2024; Fu and others 2024; Girotra and others 2023; Glickman and Sharot 2024a. There is also the potential to use AI to enhance public understanding of science (Markowitz 2024).

105 Glickman and Sharot 2024b; Peng, Garg and Kleinberg 2024; Vaccaro, Almaatouq and Malone 2024.

106 The award of the 2024 Nobel Prizes in both physics and chemistry to AI-related breakthroughs triggered some soul searching about an epistemic barrier having potentially been breaching: pattern seeking without reasoning or explanation was deemed worthy of scientific respect (Meng 2024).

107 Melumad and Yun 2025.

108 Kapoor and others 2024.

109 For evidence on complementarity, see Agarwal and others (2023), Agarwal and others (2024) and Ludwig, Mullainathan and Rambachan (2024).

110 A more rigorous way of stating AI's unique capabilities in comparison with those of humans is that it has the ability to impose mathematical structure onto unstructured data (Hofman and others 2021).

111 Abolghasemi, Ganbold and Rotaru 2025; Luo and others 2024; Karger and others 2024; Schoenegger and others 2024a; Schoenegger and others 2024b. Expert predictions are often very fraught (Grossmann and others 2024).

112 Lenton and others 2024.

113 Pyzer-Knapp and others 2022b.

114 Pyzer-Knapp and others 2022b.

115 Merchant and others 2023.

116 Toner-Rodgers 2024.

117 Agrawal, McHale and Oettl 2024; Ludwig and Mullainathan 2024; Tranchero and others 2024.

118 Data are based on the use of AI in published scholarly papers in agriculture and food sciences, art, biology, business, chemistry, computer science, economics, education, engineering, environmental sciences, geology, history, linguistics, materials science, mathematics, medicine, philosophy, physics, political science and psychology (Duede and others 2024; Xie and others 2024).

119 Koch, Stojkoski and Hidalgo 2024. More speculatively, some have argued for the

potential to use texts from the past to train large language models to enrich historical analysis (Varnum and others 2024).

120 Sakai and others 2024. For other applications in archaeology, see Cardarelli 2024. But applications of AI in archaeology have also triggered heated debates, see Huggett (2021, 2022), Cobb (2023), Gustafson (2024), Magnani and Clindaniel (2023) and Sobotkova and others (2024).

121 In December 2023 a leading journal published a review of AI applications in economics (Korinek 2023a). This review has had two updates, one in June 2024 (Korinek 2024b) and another in December 2024 (Korinek 2024a). See also Ash and Hansen (2023), Chen and others (2023b), Dell (2024) and Manning, Zhu and Horton (2024) and, in finance, Du and others (2025), Eisfeldt and Schubert (2024) and Kim, Muhn and Nikolaev (2024). Many recent studies use large language models to simulate responses by humans in surveys and behavioural science experiments using homo silicus instead of humans in economics (Filippas, Horton and Manning 2024; Manning, Zhu and Horton 2024), finance (Yang and others 2025) and political science (Argyle and others 2023; Piao and others 2025). One recent study used a collection of 1 billion synthetic personas to generate synthetic data (Ge and others 2024). Still, it is important to look at these applications with care. In psychology studies, using large language models instead of people produces falsely significant findings (Cui, Li and Zhou 2024), and Boelaert and others (2025) show that large language models respond to survey questions differently than humans. Thus, using generative AI in this way should be carefully considered and justified, not driven by the superficial anthropomorphizing perspective that large language models are like humans. It is also important to be mindful of the potential cultural biases (Atari and others 2025) or diversity of political preferences (Rozado 2024) embedded in large language models.

122 Osnabrügge, Ash and Morelli 2023; Licht 2023.

123 Nguyen and others 2024.

124 Piaggi and others 2022.

125 Reynolds and others 2025a.

126 Chakraborty and others 2024; Eggertsen and others 2025; Gao and others 2024; Mehandru and others 2025; Singh, Kaur and Gehlot 2024; Zhang and others 2024b.

127 Jiang and others 2024.

128 Antunes, Butler and Grau-Crespo 2024; Mortazavi 2025; Park, Li and Walsh 2024; Zeni and others 2025. The importance of human evaluation of AI outputs in materials science was put in sharp relief by the work of Li and others (2025), who show that training data limitations constrain the generalizability and interpretation of AI outputs in exploring new materials.

129 Romera-Paredes and others 2024.

130 Luo and others 2024. Purves (2019) explores how AI's success in playing board games is helping scientists gain new insights into the brain.

131 He 2024.

132 Abdurahman and others 2024; Feuerriegel and others 2025; Ke and others 2024; Peters and Matz 2024; Rathje and others 2024.

133 Zhang and others 2025.

134 Price and others 2024; Kochkov and others 2024. For other applications, see, for instance, Bran and others (2024), Kutz and others (2024) and Ma and others (2025). A new algorithmic architecture has also shown promise for physics-informed AI models, opening the possibility of AI that combines the best of both worlds: the ability to discern patterns in data while producing outputs constrained by the laws of physics (Liu and others 2024c; Rigas and others 2024; Urbán, Stefanou and Pons 2025).

135 Enhancing what has been described as collective intelligence (Burton and others 2024; Cui and Yasseri 2024; Gupta and others 2023; Leonard and Levin 2022; Peeters and others 2021; Riedl and others 2021; Woolley and Gupta 2024), building on insights about broader interactions between humans and machines (Brinkmann and others 2023; Pedreschi and others 2025; Rahwan and others 2019; Tsvetkova and others 2024).

136 Yan and others 2024.

137 Collins and others 2024.

138 Bail 2024; Binz and others 2025; Eger and others 2025; He and others 2023; Hullman, Holtzman and Gelman 2023; Si, Yang and Hashimoto 2024. The risk of misuse, common to AI more broadly, is a particularly serious concern, particularly in biology and drug discovery (Urbina and others 2022). One risk is related to the use of AI to write scholarly papers (Haider and others 2024; Novy-Marx and Velikov 2025).

139 Doshi and Hauser 2024; Wenger and Kenett 2025.

140 For example, 82 percent of the scientists who registered the dramatic improvement in materials discovery mentioned above also reported feeling less fulfilled in their work (Toner-Rodgers 2024; see also Ghosh and Sadeghian 2024 and Salah and others 2024).

141 Resnik and others 2025.

142 Blau and others 2024.

143 On liability challenges, see Volokh (2023). For recent journalistic accounts on debates over intellectual property, see Olson and Prince (2025) and Thornhill (2025).

144 Kapoor and Narayanan 2023; McGreivy and Hakim 2024; Rosenblatt and others 2024.

145 Messeri and Crockett 2024.

146 Ugander and Epstein (2024) emphasize the importance of randomness in creative processes. In 2023 the journal Science invited young scientists to imagine a call from an AI sentient researcher for human help: what would AI need that only humans can provide? The contributions illuminated the unique role of humans in establishing connections with people, triggering creativity by making mistakes, having perceptual capabilities, being contextual and cultural aware and being unpredictable (Heim and others 2023).

147 One innovation trap is the illusion of consensus that occurs when shared terminology creates a false impression of agreement on AI goals, even when those goals remain highly contested. This misleading consensus can divert attention from more pressing and tangible challenges in AI development. Another trap is "supercharging bad science," which refers to the way poorly defined concepts and experimental methods, often justified by the pursuit of artificial general intelligence, worsen existing problems in AI research. The lack of clear scientific rigour in these areas leads to unreliable findings and hinders meaningful progress (Blili-Hamelin and others 2025).

148 Blili-Hamelin and others (2025) pose critical questions about the direction of AI research, asking how we can ensure that its goals align with scientific, engineering and societal needs, what constitutes rigorous scientific inquiry in AI and who has the authority to shape these objectives. They argue that the research community should move away from treating artificial general intelligence as the ultimate goal of AI development.

149 AAAI 2025.

150 Wang, Hertzmann and Russakovsky 2024.

151 AAAI 2025.; Sharma 2024.

152 ETO 2024.

153 The number of scientific AI peer-reviewed articles has increased, with about 1.2 million articles released between 2017 and 2022, yet this key field is underrepresented (ETO 2024).

154 Computer vision enables machines to interpret visual data through techniques such as image recognition, object detection, facial recognition, video analysis, medical imaging and scene understanding. Closely linked to real-world applications, robotics extends AI's reach into physical systems, incorporating autonomous navigation, reinforcement learning for robotic control, humanoid robotics, swarm robotics and human–robot interaction. Natural language processing allows AI to understand and generate human language, encompassing machine translation, sentiment analysis, speech recognition, conversational AI, information retrieval and text summarization. Underpinning all these advancements is AI safety, which focuses on keeping systems robust, interpretable and aligned with human values, addressing key challenges such as adversarial resilience, fairness and bias mitigation and ensuring ethical deployment to prevent unintended harm. See Bengio and others (2024); Gyevnar and Kasirzadeh 2025.

155 ETO 2024.

156 Zhong and others 2024.

157 See Tonja and others (2024) and Zhong and others (2024).

158 UN and ILO 2024.

159 Barzelay, Ng and Romanoff 2024.

160 AI is increasingly enabling cross-border collaboration in research and innovation, fostering new networks of knowledge production across regions. One notable example is the deepening AI research collaboration between China and Singapore. Between 2016 and 2021 their joint AI publications more than doubled. Singapore has become a key hub for Chinese technology firms seeking to expand their research, investment and talent pipelines. Major players such as Alibaba, Huawei and Yitu established research outposts in the city-state during the late 2010s, often partnering with local universities or startups. This surge in colocated research and development has translated into meaningful academic collaboration: since 2010 China has been Singapore's top collaborator in AI research, with more than 10,000 coauthored AI publications—nearly double the number involving the United States. Conversely, Singapore ranks among China's top five international research partners in AI. See ETO (2023).

161 Barzelay, Ng and Romanoff 2024.

162 Human Development Report Office calculations using data retrieved in November 2024 from the Emerging Technology Observatory. The HDI classification is indicated in https://hdr.undp.org/data-center/human-development-index#/indicies/HDI.

163 Lehdonvirta, Wú and Hawkins 2024. The authors discuss the geopolitics of AI chip production (graphics processing units). They describe a division between the Compute North and Compute South, as well as Compute Deserts—distinctions based on countries' access to investment and semiconductor manufacturing. This perspective highlights the emerging global disparities in compute power and its implications for technological sovereignty and AI research and development.

164 Atari and others 2025.

165 Narayanan and Kapoor 2024.

166 UNESCO 2024.

167 Global life expectancy at birth is projected to reach 73.5 years in 2025, up from 64 years in 1990 (UNDESA 2024b.).

168 Lutz and others 2021.

169 This estimate is based on math and science and corrects for the percentage of children outside the school system (see Gust, Hanushek and Woessmann 2024b). A different global estimate indicates that 58 percent of students achieved minimum proficiency in reading by 2019 (see UNDESA 2024a).

170 Gust, Hanushek and Woessmann 2024a.

171 See table 1 in Statistical annex.

172 WHO 2021.

173 UNDP 2019.

174 Pritchett 2024.

175 Muthukrishna 2025.

176 These three categories fall in the space of higher-order thinking, which encompasses critical thinking, creative thinking and relational thinking (Miri, David and Uri 2007)

177 Normile 2025.

178 OECD 2024b.

179 Gould, Jimenez Naranjo and Balvanera 2025.

180 Molenaar 2022; Tuomi 2019.

181 Faber, Luyten and Visscher 2017.

182 Angrist and Meager 2023. A study analysing more than 200 education policies and interventions across 52 countries reveals that targeting instruction to students' learning levels, rather than to their grade level, alongside structured pedagogy, significantly improves education outcomes (Angrist and others 2024).

183 Jordan and others 2024.

184 Angrist, Bergman and Matsheng 2022.

185 Angrist and others 2023. Students who received personalized tutoring through phone calls showed significant academic gains, highlighting the effectiveness of tailored interventions alongside technology adoption and increased education spending

186 Seldon, Abidoye and Metcalf 2020.

187 Labadze, Grigolia and Machaidze 2023.

188 Rudolph and others 2024.

189 Björkegren and others 2025.

190 Henkel and others 2024.

191 De Simone 2025.

192 Alan and Mumcu 2024.

193 Smith and Livingstone 2017.

194 Ahuja and others 2025.

195 Nweje, Amaka and Makai 2025.

196 Du Boulay 2016.

197 Aldridge and others 2024.

198 Hassan and others 2024.

199 Theopilus and others 2024. A public health approach is required to allow children to enjoy the benefits of the digital world while safeguarding their mental health (Holly, Demaio and Kickbusch 2024). Although digital technologies offer benefits in multiple areas, their overuse poses psychological, social and ethical challenges. To mitigate these challenges, schools and parents can implement digital wellbeing practices (George and Shaji 2024).

200 Beuermann and others 2015; Meza-Cordero 2017.

201 A randomized controlled trial in Kenya found no meaningful medium-run impacts on children's education or household wellbeing (consumption and expenditure, income and earnings, asset ownership and wealth accumulation, employment and labour force participation) from expanding electric grid infrastructure in rural Kenya, and it could be because of credit constraints, bureaucratic red tape, low reliability and leakage, which, as noted in chapter 1, could be related to the lack of complementary assets that could make good use of electricity (Lee, Miguel and Wolfram 2020).

202 Muralidharan, Singh and Ganimian 2019.

203 Atkinson and others 2019.

204 OECD 2023b.

205 Ishida, Ihsan and Rudawan 2024.

206 Farahani and Ghasemi 2024.

207 OECD 2024a.

208 Khajeh Naeeni and Nouhi 2024.

209 Mollick and Mollick 2023.

210 Ijaz, Bogdanovych and Trescak 2017.

211 C. Gu and others 2024; X. Gu and others 2024.

212 Beg and others 2022. For example, two randomized controlled trials in Pakistan found that combining teacher engagement with curriculum-based videos improved students' test scores more than using videos alone (Beg and others 2022).

213 Ertmer and Ottenbreit-Leftwich 2010.

214 Angrist and Dercon 2024; Moundridou, Matzakos and Doukakis 2024. See also Bewersdorff and others (2025).

215 Tan and others 2024.

216 Kirkpatrick, Rivera and Akers 2022.

217 Sedek 2021.

218 Bastani and others 2024.

219 Loeckx 2016.

220 Koedinger, Corbett and Perfetti 2012.

221 Koedinger, Corbett and Perfetti 2012.

222 Mollick and others 2024.

223 Sperling and others 2022.

224 Mayer and DaPra 2012.

225 Lacity and Willcocks 2017.

226 Selwyn 2019.

227 Fan and others 2025.

228 Topol 2024.

229 Liu and others 2025; Zhang and others 2024a.

230 Topol 2023.

231 Bekbolatova and others 2024; Wachter and Brynjolfsson 2024.

232 Wang and Preininger 2019.

233 For example, AI is used in obstetric diagnostics, such as foetal cardiotocography and ultrasonography (Kim, Cho and Kwon 2022). Learning-based inference of longitudinal image changes, a machine learning method, could accurately quantify relevant individual-level changes in longitudinal imaging data, offering valuable insights for studying temporal mechanisms or guiding clinical decisions (Kim and others 2025). AI has also been deployed to identify neurocognitive changes in hard-to-access regions of the brain to diagnose neurodegenerative diseases (Yin and others 2025). Along with sensors, AI has been deployed in applications ranging from monitoring dietary intake (Park and others 2024to sleep patterns (Tang and others 2025). More recent applications leverage generative AI to enhance disease diagnosis and treatment

(Pierson and others 2025; Takita and others 2025). For example, a recent study found GPT-4 diagnosed illnesses with 90 percent accuracy, surpassing physicians at 74 percent without AI and 76 percent with chatbot assistance, showcasing AI's potential to improve diagnostics (Kolata 2024).

234 Ferdousi, Hossain and El Saddik 2021. AI-assisted healthcare systems strengthen delivery by enabling collaboration, information sharing and the use of electronic health records (Palmer and others 2018). For example, AI tools such as CC-Cruiser for childhood cataract diagnosis and Endoangel for colonoscopy monitoring show how machine learning can improve workflows and diagnostics (Lin and others 2019). AI can also improve the detection of small bowel bleeding lesions, offering faster and more accurate results than traditional methods (Spada and others 2024).

235 WHO 2024. For example, AI has improved prediction of ischemic heart disease risk by integrating clinical records, biomarkers and imaging. Advanced diagnostic tools such as four-dimensional flow magnetic resonance imaging and hybrid systems (including positron emission tomography/magnetic resonance imaging) provide a comprehensive understanding of cardiac health. AI's ability to analyse electrocardiograms, echocardiography and coronary angiography shows promise in enhancing healthcare, especially in low-income countries with limited access to specialized expertise (Uzokov and others 2024).

236 Bailey and others 2024.

237 Chaix and others 2019.

238 A review of 26 randomized controlled trials across multiple countries found that mobile interventions significantly reduced hospitalization rates in heart failure patients and lowered systolic blood pressure in hypertension patients (Indraratna and others 2020) Furthermore, AI-powered platforms, including facial recognition and computer vision, can also monitor medication adherence for schizophrenia (Bain and others 2017).

239 Uzokov and others 2024.

240 Adapa and others 2025.

241 Alcazer and others 2024. See also Esteva and others (2017), Gulshan and others (2016), Hannun and others (2019) and Rajpurkar and others (2018).

242 Turki, Engelke and Sobas 2024.

243 Khan and others 2022b.

244 Puja and others 2024.

245 Towfek and Elkanzi 2024. See also Kraemer and others (2025).

246 For health specifically, see Sagona and others (2025) and Tejani and others (2024). For trust in AI more generally, see Afroogh and others (2024) and von Eschenbach (2021).

247 Dychiao and others 2024.

248 Saliba and others 2012; Scott Kruse and others 2018.

249 Celi and others 2022.

250 Sarkar and others 2024.

251 UN and ILO 2024.

252 Parsa and others 2023.

253 d'Elia and others 2022.

254 WHO 2022.

255 Moyer and others 2018.

256 Roopaei and others 2021.

257 Singh 2024.

258 Zhu and others 2024.

259 Shandhi and others 2024.

260 For example, see Han and others' (2024) recent scoping review of randomized controlled trials of AI in clinical practice.

261 Obi and others 2024.

262 OECD 2023a.

263 Liu and others 2021.

264 Hosny and Sollaci 2022.

265 Denniston and Liu 2024.

266 Goh and others 2024.

267 Rotenstein and Wachter 2024. Furthermore, A study of 1,600 emergency medical records found large language model–generated handoff notes superior in automated evaluations but slightly inferior in safety, emphasizing the need for a physician-in-loop design (Hartman and others 2024)

268 Liu and others 2024a.

269 Capraro and others 2024.

270 Lenharo 2024.

271 Phillips and others 2019.

272 Seyyed-Kalantari and others 2021. For example, systems such as Michigan Medicine's AI for sepsis diagnosis have faced issues due to poor calibration across different settings (Gichoya and others 2023.), highlighting the need for better transparency and accountability.

273 Rajpurkar and others 2022.

274 Sjoding and others 2020.

275 Slawomirski and others 2023.

276 Norori and others 2021.

277 Wilhelm, Steckelberg and Rebitschek 2025.

278 Wei and others 2024.

279 Ueda and others 2024.

280 Chen and others 2023a.

281 Sandoval-Almazan, Millan-Vargas and Garcia-Contreras 2024.

282 Moura and others 2024.

283 Rosenbacke and others 2024.

284 Platt and others 2024.

285 Shevtsova and others 2024.

286 Gille, Jobin and Ienca 2020.

287 Singh 2024. Singh 2024.

288 Singh 2024. Singh 2024.

289 Lara-Cinisomo and others 2021. Lara-Cinisomo and others 2021.

290 Soto and others 2018. Soto and others 2018.

291 Frank and others 2021. Frank and others 2021.

292 For example, using data from European subnational regions and districts, Antonietti, Burlina and Rodriguez-Pose (2025) found that strong formal institutions (effective governance) and informal institutions (bridging social capital, trust) were key determinants of whether digital technologies exacerbated economic divides or brought more equitable economic outcomes.

293 Imbs and Wacziarg 2003.

294 Oxford Insights 2024.

295 As indicated by the economic complexity assessment (Harvard Growth Lab 2025).

296 See, for example, the latest United Nations Conference on Trade and Development State of Commodity Dependence report (UNCTAD 2023).

297 Mishra and others 2023.

298 Diouf and others 2024.

299 Rodrik 2016; Rodrik and Sandhu 2024. For low and medium HDI countries traditional development pathways—adopting existing technologies and leveraging relatively "cheap" labour to compete in international markets—have been framed by the expectation of convergence with higher-income countries. But actual outcomes have been far more complex: while some countries have seized these opportunities, convergence with very high HDI countries through traditional manufacturing- and export-led strategies has not materialized for a considerable number of countries. Indeed, many countries are now experiencing shifts to predominantly service-based economies at lower incomes (Rodrik 2016)

300 Empowerment includes fostering digital literacy and algorithmic awareness, enabling individuals to understand and critically evaluate AI's broader implications in their lives (Washington 2023).

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CHAPTER 4

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CHAPTER 5

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Statistical annex

Statistical annex

Readers guide

The tables provide an overview of key aspects of human development. The seven tables contain the family of composite human development indices and their components estimated by the Human Development Report Office (HDRO). The sixth table, on multidimensional poverty, is produced in partnership with the Oxford Poverty and Human Development Initiative.

Tables 1–7 are part of the 2025 Human Development Report. The full set of seven statistical tables is available for download at https://hdr.undp.org/en/human-development-report-2025. Unless otherwise noted, tables use data available to the HDRO as of 1 November 2024. All indices and indicators, along with technical notes on the calculation of composite indices and additional source information, are available at https://hdr.undp.org/data-center.

Countries and territories are ranked by 2023 Human Development Index (HDI) value. Robustness and reliability analysis has shown that for most countries differences in HDI are not statistically significant at the fourth decimal place. For this reason countries with the same HDI value at three decimal places are listed with tied ranks.

Sources and definitions

Unless otherwise noted, the HDRO uses data from international data agencies with the mandate, resources and expertise to collect national data on specific indicators.

Definitions of indicators and sources for original data components are given at the end of each table, with full source details in *Statistical references*.

Gross national income per capita in purchasing power parity terms

In comparing standard of living across countries, the income component of the HDI uses gross national income (GNI) per capita converted into purchasing power parity (PPP) terms to eliminate differences in national price levels.

The 2021 cycle of the International Comparison Programme survey, which is the world's largest statistical initiative and coordinated by the World Bank, produced internationally comparable price level indices and estimates of PPP-based gross domestic product and its major expenditure components in aggregate and per capita terms for 176 participating economies. The 2025 Human Development Report uses GNI per capita in constant 2021 PPP terms.

Methodology updates

The 2025 Report retains all the composite indices from the family of human development indices—the HDI, the Inequality-adjusted Human Development Index (IHDI), the Gender Development Index (GDI), the Gender Inequality Index (GII), the Multidimensional Poverty Index (MPI) and the Planetary pressures-adjusted Human Development Index (PHDI). The methodology used to compute the indices is the same as the one used in the 2023/2024 Human Development Report. For details, see *Technical notes 1–6* at https://hdr.undp.org/sites/default/files/2025_HDR/hdr2025_technical_notes.pdf.

Comparisons over time and across editions

Because national and international agencies continually improve their data series, the data—including the HDI values and ranks—presented in this report are not comparable to those published in earlier editions. For HDI comparability across years and countries, see table 2, which presents trends using consistent data, or https://hdr.undp.org/data-center, which presents interpolated consistent data.

Discrepancies between national and international estimates

National and international data can differ because international agencies harmonize national data using a consistent methodology and occasionally produce estimates of missing data to allow comparability across countries. In other cases international agencies might not have access to the most recent national data. When HDRO becomes aware of discrepancies, it brings them to the attention of national and international data authorities.

Country groupings and aggregates

The tables present weighted aggregates for several country groupings. In general, an aggregate is shown only when data are available for at least half the countries and represent at least two-thirds of the population in that grouping. Aggregates for each grouping cover only the countries for which data are available.

Human development classification

HDI classifications are based on HDI fixed cutoff points, which are derived from the quartiles of distributions of the component indicators. The cutoff points are HDI of less than 0.550 for low human development, 0.550–0.699 for medium human development, 0.700–0.799 for high human development and 0.800 or greater for very high human development.

Regional groupings

Regional groupings are based on United Nations Development Programme regional classifications. Least Developed Countries and Small Island Developing States are defined according to UN classifications (see https://www.un.org/ohrlls/).

Developing countries

The aggregates for developing countries are based on information from all developing countries that are included in a regional grouping.

Organisation for Economic Co-operation and Development

Of the 38 Organisation for Economic Co-operation and Development members, 33 are considered developed countries and 5 (Costa Rica, Chile, Colombia, Mexico and Türkiye) are considered developing countries. Aggregates refer to all countries from the group for which data are available.

Country notes

Data for China do not include Hong Kong Special Administrative Region of China, Macao Special Administrative Region of China or Taiwan Province of China.

As of 2 May 2016, Czechia is the short name to be used for the Czech Republic.

As of 1 June 2018, the Kingdom of Eswatini is the name of the country formerly known as Swaziland.

As of 14 February 2019, the Republic of North Macedonia (short form: North Macedonia) is the name of the country formerly known as the former Yugoslav Republic of Macedonia.

As of 1 June 2022, Türkiye is the name of the country formerly known as Turkey.

Symbols

A dash between two years, as in 2010–2023, indicates that the data are from the most recent year available during the period specified. Growth rates are usually average annual rates of growth between the first and last years of the period shown.

The following symbols are used in the tables:

..	Not available
0 or 0.0	Nil or negligible
—	Not applicable

Statistical acknowledgements

The Report's composite indices and other statistical resources draw on a wide variety of the most respected international data providers in their specialized fields. HDRO is particularly grateful to Eurostat; the Global Carbon Project; ICF Macro; the International Labour Organization; the International Monetary Fund; the Inter-Parliamentary Union; the Luxembourg Income Study; the Organisation for Economic Co-operation and Development; the Socio-Economic Database for Latin America and the Caribbean; the United Nations Children's Fund; the United Nations Department of Economic and Social Affairs; the United Nations Educational, Scientific and Cultural Organization Institute for Statistics; the United Nations Environment Programme; the United Nations Statistics Division; the United Nations University World Institute for Development Economics Research; the World Bank; the World Health Organization; and the World Inequality Database. The international education database maintained by Robert Barro (Harvard University) and Jong-Wha Lee (Korea University) was another invaluable source for the calculation of the Report's indices.

Statistical tables

The seven tables relate to the six composite human development indices and their components. Since the 2010 Human Development Report, four composite human development indices—the HDI, the IHDI, the GII and the MPI for developing countries—have been calculated. The 2014 Report introduced the GDI, which compares the HDI calculated separately for women and men. The 2020 Report introduced the PHDI, which adjusts the HDI for the excessive human pressure on the planet.

For indicators that are global Sustainable Development Goals indicators or can be used in monitoring progress towards specific goals, the table headers include the relevant goals and targets.

Table 1, Human Development Index and its components, ranks countries by 2023 HDI value and details the values of the three HDI components: longevity, education (with two indicators) and income per capita. The table also presents the difference in rankings by HDI value and gross national income per capita, as well as the rank on the 2022 HDI, calculated using the most recently revised historical data available in 2024.

Table 2, Human Development Index trends, 1990–2023, provides a time series of HDI values allowing 2023 HDI values to be compared with those for previous years. The table uses the most recently revised historical data available in 2024 and the same methodology applied to compute 2023 HDI values. The table also includes the change in HDI rank over the last eight years and the average annual HDI growth rate across four time intervals: 1990–2000, 2000–2010, 2010–2023 and 1990–2023.

Table 3, Inequality-adjusted Human Development Index, contains two related measures of inequality—the IHDI and the overall loss in HDI due to inequality. The IHDI looks beyond the average achievements of a country in longevity, education and income to show how these achievements are distributed among its residents. The IHDI value can be interpreted as the level of human development when inequality is accounted for. The relative difference between IHDI and HDI values is the loss due to inequality in distribution of the HDI within the country. The table presents the coefficient of human inequality, which is the unweighted average of inequalities in the three dimensions. In addition, the table shows each country's difference in rank on the HDI and the IHDI. A negative value means that taking inequality into account lowers a country's rank on the HDI. The table also presents the income shares of the poorest 40 percent, the richest 10 percent and the richest 1 percent of the population, as well as the Gini coefficient.

Table 4, Gender Development Index, measures disparities on the HDI by gender. The table contains HDI values estimated separately for women and men, the ratio of which is the GDI value. The closer the ratio is to 1, the smaller the gap between women and men. Values for the three HDI components—longevity, education (with two indicators) and income per capita—are also presented by gender. The table includes five country groupings by absolute deviation from gender parity in HDI values.

Table 5, Gender Inequality Index, presents a composite measure of gender inequality using three dimensions: reproductive health, empowerment and the labour market. The reproductive health indicators are maternal mortality ratio and adolescent birth rate. The empowerment indicators are the percentage of parliamentary seats held by women and the percentage of population with at least some secondary education by gender. The labour market indicator is participation in the labour force by gender. A low GII value indicates low inequality between women and men, and vice-versa.

Table 6, Multidimensional Poverty Index, captures the multiple deprivations that people in developing countries face in their health, education and standard of living. The MPI shows both the incidence of nonincome multidimensional poverty (a headcount of those in multidimensional poverty) and its intensity (the average deprivation score experienced by multidimensionally poor people). Based on deprivation score thresholds, people are classified as multidimensionally poor, in severe multidimensional poverty or vulnerable to multidimensional poverty. The table includes the contribution of deprivation in each dimension to overall multidimensional poverty. It also presents measures of income poverty—population living below the national poverty line and population living on less than $2.15 in purchasing power parity terms per day.

Table 7, Planetary pressures-adjusted Human Development Index, adjusts the HDI for planetary pressures in the Anthropocene to reflect a concern for intergenerational inequality, similar to the Inequality-adjusted HDI adjustment, which is motivated by a concern for intragenerational inequality. The PHDI value can be interpreted as the level of human development adjusted by carbon dioxide emissions per person (production-based) and material footprint per capita to account for the excessive human pressure on the planet. The table presents the relative difference between PHDI and HDI values as well as each country's difference in rank on the HDI and the PHDI. A negative value means that taking planetary pressures into account lowers a country's rank on the HDI.

Human development composite indices

TABLE 1

Human Development Index and its components

HDI RANK		Human Development Index (HDI)	SDG 3 Life expectancy at birth	SDG 4.3 Expected years of schooling	SDG 4.4 Mean years of schooling	SDG 8.5 Gross national income (GNI) per capita	GNI per capita rank minus HDI rank	HDI rank
		Value	(years)	(years)	(years)	(2021 PPP $)		
		2023	2023	2023[a]	2023[a]	2023	2023[b]	2022
Very high human development								
1	Iceland	0.972	82.7	18.9[c]	13.9[d]	69,117	12	3
2	Norway	0.970	83.3	18.8[c]	13.1[e]	112,710[f]	0	1
2	Switzerland	0.970	84.0	16.7	13.9[e]	81,949[f]	5	2
4	Denmark	0.962	81.9	18.7[c]	13.0[e]	76,008[f]	4	4
5	Germany	0.959	81.4	17.3	14.3[e]	64,053	13	6
5	Sweden	0.959	83.3	19.0[c]	12.7[e]	66,102	10	4
7	Australia	0.958	83.9	20.7[c]	12.9	58,277	14	8
8	Hong Kong, China (SAR)	0.955	85.5[g]	16.9	12.4	69,436	4	9
8	Netherlands	0.955	82.2	18.6[c]	12.7[e]	68,344	6	7
10	Belgium	0.951	82.1	19.0[c]	12.7[e]	63,582	9	13
11	Ireland	0.949	82.4	19.2[c]	11.7[e]	90,885[f]	-6	10
12	Finland	0.948	81.9	19.5[c]	13.0[e]	57,068	10	11
13	Singapore	0.946	83.7	16.7	12.0	111,239[f]	-10	14
13	United Kingdom	0.946	81.3	17.8	13.5	54,372	13	11
15	United Arab Emirates	0.940	82.9	15.6	13.0	71,142	-4	23
16	Canada	0.939	82.6	15.9	13.9	54,688	9	16
17	Liechtenstein	0.938	83.6	15.4	12.4[h]	166,812[f,i]	-16	15
17	New Zealand	0.938	82.1	19.3[c]	12.9[e]	47,260	17	17
17	United States	0.938	79.3	15.9	13.9	73,650	-7	18
20	Korea (Republic of)	0.937	84.3	16.6	12.7[e]	49,726	11	19
21	Slovenia	0.931	81.6	17.5	13.0[e]	46,361	15	21
22	Austria	0.930	82.0	16.3	12.4[e]	63,479	-2	20
23	Japan	0.925	84.7	15.5	12.7[e]	47,775	10	23
24	Malta	0.924	83.3	15.9	12.4[e]	52,155	5	26
25	Luxembourg	0.922	82.2	14.4	12.6[d]	85,461[f]	-19	22
26	France	0.920	83.3	16.1	11.8[e]	55,060	-2	27
27	Israel	0.919	82.4	14.9	13.5[e]	48,050	5	23
28	Spain	0.918	83.7	17.8	10.8[e]	46,008	9	28
29	Czechia	0.915	79.8	16.8	13.0[e]	45,889	9	28
29	Italy	0.915	83.7	16.7	10.8[e]	52,389	-1	32
29	San Marino	0.915	85.7[g]	14.6[e]	11.4	64,706	-13	30
32	Andorra	0.913	84.0	14.5	11.6	64,631	-15	37
32	Cyprus	0.913	81.6	16.2	12.6[e]	45,394	7	31
34	Greece	0.908	81.9	20.8[c]	11.6[e]	35,761	17	36
35	Poland	0.906	78.6	16.7	13.2[e]	42,218	5	33
36	Estonia	0.905	79.2	16.0	13.6[e]	40,881	8	33
37	Saudi Arabia	0.900	78.7	16.9	11.6[e]	50,299	-7	37
38	Bahrain	0.899	81.3	15.9	11.1	52,819	-11	33
39	Lithuania	0.895	76.0	16.5	13.6[e]	41,916	2	39
40	Portugal	0.890	82.4	17.5	9.7[e]	41,064	3	41
41	Croatia	0.889	78.6	16.3	12.1[j]	41,380	1	40
41	Latvia	0.889	76.2	16.5	13.4[e]	37,998	6	43
43	Qatar	0.886	82.4	13.1	10.8	105,353[f]	-39	41
44	Slovakia	0.880	78.3	14.9	13.1[e]	36,793	5	44
45	Chile	0.878	81.2	16.9	11.3[e]	28,047	16	45
46	Hungary	0.870	77.0	15.5	12.3[e]	37,236	2	46
47	Argentina	0.865	77.4	18.8[c]	11.2[e]	25,876	20	47
48	Montenegro	0.862	77.1	15.5	12.8[e]	28,026	14	48
48	Uruguay	0.862	78.1	17.5	10.5	28,650	12	50
50	Oman	0.858	80.0	13.4	11.9	36,096	0	52
51	Türkiye	0.853	77.2	19.8[c]	9.0[e]	34,507	1	48
52	Kuwait	0.852	80.4	15.9[e]	7.6[e]	56,612	-29	53
53	Antigua and Barbuda	0.851	77.6	15.5[e]	11.6	27,387	10	51
54	Seychelles	0.848	72.9	18.2[c]	11.2	29,195	4	56
55	Bulgaria	0.845	75.6	15.3	11.5[e]	32,175	0	57
55	Romania	0.845	75.9	14.1	11.6	39,374	-10	54
57	Georgia	0.844	74.5	16.8	12.7	20,753	18	55
58	Saint Kitts and Nevis	0.840	72.1	18.4[b,k]	10.8[l]	29,105	1	60
59	Panama	0.839	79.6	13.3[e]	10.8[e]	34,385	-6	57
60	Brunei Darussalam	0.837	75.3	13.7[m]	9.3	75,827[f]	-51	63
60	Kazakhstan	0.837	74.4	14.0	12.5[e]	30,989	-4	59
62	Costa Rica	0.833	80.8	16.3[e]	8.8[e]	23,417	6	65

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HDI RANK		Human Development Index (HDI)	Life expectancy at birth	Expected years of schooling	Mean years of schooling	Gross national income (GNI) per capita	GNI per capita rank minus HDI rank	HDI rank
			SDG 3	SDG 4.3	SDG 4.4	SDG 8.5		
		Value	(years)	(years)	(years)	(2021 PPP $)		
		2023	2023	2023[a]	2023[a]	2023	2023[b]	2022
62	Serbia	0.833	76.8	15.0	11.6[e]	23,115	7	61
64	Russian Federation	0.832	73.2	13.2	12.4	39,222	-18	61
65	Belarus	0.824	74.4	13.7	12.3[e]	26,725	1	64
66	Bahamas	0.820	74.6	11.9[n]	12.8[e]	30,975	-9	66
67	Malaysia	0.819	76.7	12.7	11.1	32,553	-13	68
68	North Macedonia	0.815	77.4	14.8	10.2[m]	22,128	2	67
69	Armenia	0.811	75.7	14.4	11.3[d]	20,221	9	72
69	Barbados	0.811	76.2	16.6[e]	9.9[d]	17,328	20	69
71	Albania	0.810	79.6	14.5	10.2[d]	17,627	16	70
72	Trinidad and Tobago	0.807	73.5	14.2[o]	10.8	27,000	-7	71
73	Mauritius	0.806	74.9	14.2[e]	10.1[d]	27,280	-9	75
74	Bosnia and Herzegovina	0.804	77.9	13.2	11.0	19,827	6	73
High human development								
75	Iran (Islamic Republic of)	0.799	77.7	14.0[e]	10.8[e]	16,096	19	77
76	Saint Vincent and the Grenadines	0.798	71.2	16.3[n]	11.3[p]	17,247	14	75
76	Thailand	0.798	76.4	15.4[e]	9.0	20,570	1	78
78	China	0.797	78.0	15.5[e]	8.0[e]	22,029	-7	74
79	Peru	0.794	77.7	14.9[e]	10.2[e]	14,339	23	79
80	Grenada	0.791	75.2	16.6[e]	9.4[q]	14,349	21	80
81	Azerbaijan	0.789	74.4	12.9	11.1	20,668	-5	82
81	Mexico	0.789	75.1	14.5	9.3[e]	21,813	-8	84
83	Colombia	0.788	77.7	14.3	9.0[e]	18,666	1	85
84	Brazil	0.786	75.8	15.8	8.4[e]	18,011	1	86
84	Palau	0.786	69.3	14.1	13.3[p]	16,035	11	81
86	Moldova (Republic of)	0.785	71.2	14.6[e]	11.8	15,867	11	82
87	Ukraine	0.779	73.4	13.3	11.1[d]	16,933	5	90
88	Ecuador	0.777	77.4	14.9	9.0	13,986	15	89
89	Dominican Republic	0.776	73.7	13.6	9.4[e]	22,024	-17	87
89	Guyana	0.776	70.2	13.0[o]	8.7[d]	46,959	-54	95
89	Sri Lanka	0.776	77.5	13.1	10.8	12,616	22	88
92	Tonga	0.769	72.9	17.8[e]	10.9[d]	7,438	38	91
93	Maldives	0.766	81.0	12.8	7.4[d]	19,317	-11	91
93	Viet Nam	0.766	74.6	15.5	9.0	13,033	14	91
95	Turkmenistan	0.764	70.1	13.2	11.2[e]	17,716	-9	96
96	Algeria	0.763	76.3	15.5	7.4[e]	15,114	3	96
97	Cuba	0.762	78.1	13.9	10.6[d]	8,415[r]	30	91
98	Dominica	0.761	71.1	14.2[e]	10.1	16,001	-2	98
99	Paraguay	0.756	73.8	14.0[e]	8.9[e]	15,252	-1	102
100	Egypt	0.754	71.6	13.1[e]	10.1[e]	16,218	-7	100
100	Jordan	0.754	77.8	13.1	10.2	9,222	22	100
102	Lebanon	0.752	77.8	11.7	10.4[s]	11,299	13	99
103	Saint Lucia	0.748	72.7	12.7	8.6[e]	20,900	-29	102
104	Mongolia	0.747	71.7	13.6	9.4[m]	14,787	-4	105
105	Tunisia	0.746	76.5	14.7[e]	7.6	12,011	9	104
106	South Africa	0.741	66.1	13.8	11.6	13,694	0	107
107	Uzbekistan	0.740	72.4	12.5	11.9	8,826	17	107
108	Bolivia (Plurinational State of)	0.733	68.6	15.6[e]	10.0[e]	9,445	13	113
108	Gabon	0.733	68.3	12.5[e]	9.7	18,854	-25	111
108	Marshall Islands	0.733	66.9	16.4	11.6[p]	7,224	23	110
111	Botswana	0.731	69.2	11.4	10.5	16,984	-20	112
111	Fiji	0.731	67.3	13.8	10.4	12,843	-3	114
113	Indonesia	0.728	71.1	13.3	8.7[e]	13,700	-8	114
114	Suriname	0.722	73.6	11.0	8.4[e]	17,344	-26	116
115	Belize	0.721	73.6	12.0	8.8	12,343	-2	118
115	Libya	0.721	69.3	12.9[q]	7.8[l]	19,831	-36	106
117	Jamaica	0.720	71.5	12.4[e]	10.0	10,057[t]	2	117
117	Kyrgyzstan	0.720	71.7	12.7	12.1[e]	6,078	24	118
117	Philippines	0.720	69.8	12.8[e]	10.0	10,731	0	120
120	Morocco	0.710	75.3	15.1	6.2	8,653	5	122
121	Venezuela (Bolivarian Republic of)	0.709	72.5	13.0[p]	9.7[p]	7,157[u]	11	121
122	Samoa	0.708	71.7	12.4	11.3[e]	5,952	21	123
123	Nicaragua	0.706	74.9	11.5	9.9	6,881	11	124
124	Nauru	0.703	62.1	12.8[q]	9.4[q]	19,642	-43	125

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HDI RANK		Human Development Index (HDI)	Life expectancy at birth	Expected years of schooling	Mean years of schooling	Gross national income (GNI) per capita	GNI per capita rank minus HDI rank	HDI rank
			SDG 3	SDG 4.3	SDG 4.4	SDG 8.5		
		Value	(years)	(years)	(years)	(2021 PPP $)		
		2023	2023	2023[a]	2023[a]	2023	2023[b]	2022
Medium human development								
125	**Bhutan**	0.698	73.0	13.2 [e]	5.8 [l]	13,843	-21	126
126	**Eswatini (Kingdom of)**	0.695	64.1	15.2 [e]	8.7	9,919	-6	126
126	**Iraq**	0.695	72.3	12.4 [v]	6.8 [o]	12,654	-16	126
128	**Tajikistan**	0.691	71.8	10.8 [e]	11.3 [d]	5,747	17	129
129	**Tuvalu**	0.689	67.1	12.4 [w]	10.8 [e]	7,006	4	130
130	**Bangladesh**	0.685	74.7	12.3	6.8	8,498	-4	131
130	**India**	0.685	72.0	13.0	6.9	9,047	-7	133
132	**El Salvador**	0.678	72.1	11.1	7.3	10,595	-14	134
133	**Equatorial Guinea**	0.674	63.7	12.5 [q]	8.3 [l]	12,762	-24	132
133	**Palestine, State of**	0.674	65.2	13.0	10.1	6,547	5	109
135	**Cabo Verde**	0.668	76.1	11.4 [e]	6.1 [l]	8,165	-7	135
136	**Namibia**	0.665	67.4	11.8 [x]	7.3 [d]	10,917	-20	137
137	**Guatemala**	0.662	72.6	10.7	5.8	12,459	-25	136
138	**Congo**	0.649	65.8	12.7 [e]	8.3 [d]	5,903	6	138
139	**Honduras**	0.645	72.9	10.2 [e]	7.5 [e]	6,065	3	139
140	**Kiribati**	0.644	66.5	11.9 [y]	9.1 [l]	4,947	11	140
141	**Sao Tome and Principe**	0.637	69.7	12.9 [o]	6.0 [e]	5,583	6	141
142	**Timor-Leste**	0.634	67.7	13.3 [x]	6.2 [x]	5,435	8	142
143	**Ghana**	0.628	65.5	11.4	7.1	6,846	-8	144
143	**Kenya**	0.628	63.6	11.5 [x]	8.6	5,608	3	143
145	**Nepal**	0.622	70.4	13.8	4.5	4,726	10	150
146	**Vanuatu**	0.621	71.5	11.8 [e]	7.2 [l]	3,404	20	145
147	**Lao People's Democratic Republic**	0.617	69.0	9.6	6.1 [d]	8,106	-18	147
148	**Angola**	0.616	64.6	12.2	6.0 [x]	6,631	-11	146
149	**Micronesia (Federated States of)**	0.615	67.2	11.5 [q]	7.3 [l]	4,246	7	147
150	**Myanmar**	0.609	66.9	11.5 [s]	6.4 [z]	4,919 [aa]	3	149
151	**Cambodia**	0.606	70.7	11.2	5.2	4,931	1	151
152	**Comoros**	0.603	66.8	13.3 [e]	6.0	3,481	12	151
153	**Zimbabwe**	0.598	62.8	11.1 [e]	8.9 [e]	3,511	9	153
154	**Zambia**	0.595	66.3	11.0 [ab]	7.4 [d]	3,447	11	154
155	**Cameroon**	0.588	63.7	10.8	6.6 [d]	4,746	-1	156
156	**Solomon Islands**	0.584	70.5	11.3 [q]	5.9 [l]	2,777	18	155
157	**Côte d'Ivoire**	0.582	61.9	11.4	4.9	6,735	-21	162
157	**Uganda**	0.582	68.3	11.6 [x]	6.3 [e]	2,736	18	157
159	**Rwanda**	0.578	67.8	12.6	4.9	2,971	9	160
160	**Papua New Guinea**	0.576	66.1	11.5 [x]	5.0 [d]	3,971	-2	158
161	**Togo**	0.571	62.7	13.1 [e]	5.9 [e]	2,856	9	161
162	**Syrian Arab Republic**	0.564	72.1	7.4 [n]	5.9 [p]	3,918	-3	159
163	**Mauritania**	0.563	68.5	7.9 [e]	4.9 [d]	6,267	-23	163
164	**Nigeria**	0.560	54.5	10.5	7.6	5,569	-16	164
165	**Tanzania (United Republic of)**	0.555	67.0	8.6	6.1	3,515	-4	165
166	**Haiti**	0.554	64.9	10.9 [q]	5.4 [ac]	2,935	3	166
167	**Lesotho**	0.550	57.4	11.0 [e]	7.7 [e]	3,029	0	167
Low human development								
168	**Pakistan**	0.544	67.6	7.9 [e]	4.3 [e]	5,501	-19	168
169	**Senegal**	0.530	68.7	9.1	2.9 [e]	4,202	-12	169
170	**Gambia**	0.524	65.9	9.0 [x]	4.7 [x]	2,812	1	170
171	**Congo (Democratic Republic of the)**	0.522	61.9	10.9 [e]	7.4 [d]	1,431	17	172
172	**Malawi**	0.517	67.4	9.9	5.2 [m]	1,634	12	173
173	**Benin**	0.515	60.8	10.4	3.2	3,806	-13	174
174	**Guinea-Bissau**	0.514	64.1	10.6 [o]	3.7	2,403	2	175
175	**Djibouti**	0.513	66.0	6.2 [e]	4.0 [p]	6,368	-36	176
176	**Sudan**	0.511	66.3	8.6 [e]	4.0	2,810	-4	171
177	**Liberia**	0.510	62.2	10.5	6.2 [e]	1,538	9	177
178	**Eritrea**	0.503	68.6	7.3 [e]	5.1 [l]	2,029	1	178
179	**Guinea**	0.500	60.7	10.4 [e]	2.5 [e]	3,494	-16	179
180	**Ethiopia**	0.497	67.3	9.2 [x]	2.4 [e]	2,796	-7	181
181	**Afghanistan**	0.496	66.0	10.8 [e]	2.5	1,972	-1	180
182	**Mozambique**	0.493	63.6	10.8 [e]	4.6	1,356	7	182
183	**Madagascar**	0.487	63.6	9.1 [e]	4.6	1,656	0	183
184	**Yemen**	0.470	69.3	7.5 [p]	5.5	1,018	7	184
185	**Sierra Leone**	0.467	61.8	9.1 [o]	3.5 [e]	1,714	-3	185

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HDI RANK		Human Development Index (HDI) Value 2023	SDG 3 Life expectancy at birth (years) 2023	SDG 4.3 Expected years of schooling (years) 2023[a]	SDG 4.4 Mean years of schooling (years) 2023[a]	SDG 8.5 Gross national income (GNI) per capita (2021 PPP $) 2023	GNI per capita rank minus HDI rank 2023[b]	HDI rank 2022
186	Burkina Faso	0.459	61.1	8.7	2.3	2,391	-9	186
187	Burundi	0.439	63.7	9.8 [e]	3.5 [e]	859	5	187
188	Mali	0.419	60.4	7.0 [e]	1.6 [m]	2,342	-10	188
188	Niger	0.419	61.2	8.3 [e]	1.4 [d]	1,590	-3	189
190	Chad	0.416	55.1	8.3 [e]	2.3 [e]	1,748	-9	189
191	Central African Republic	0.414	57.4	7.4 [e]	4.0 [d]	1,100	-1	..
192	Somalia	0.404	58.8	7.5 [q]	1.9	1,475	-5	192
193	South Sudan	0.388	57.6	5.6 [e]	5.7 [ad]	688	0	191
Other countries or territories								
	Korea (Democratic People's Rep. of)	..	73.6	12.2 [e]	..	..	..	..
	Monaco	..	86.4 [g]	21.7 [c]	..	..	..	..
Human development groups								
	Very high human development	0.914	80.0	16.4	12.5	53,014	–	–
	High human development	0.777	75.7	14.6	8.7	18,405	–	–
	Medium human development	0.656	69.3	12.1	6.8	7,822	–	–
	Low human development	0.515	65.0	8.9	4.0	3,007	–	–
Developing countries		0.712	72.0	12.7	7.8	13,301	–	–
Regions								
	Arab States	0.719	72.5	12.0	8.1	15,825	–	–
	East Asia and the Pacific	0.775	75.9	14.6	8.3	19,520	–	–
	Europe and Central Asia	0.818	74.8	15.6	10.7	23,171	–	–
	Latin America and the Caribbean	0.783	75.6	14.8	9.1	18,048	–	–
	South Asia	0.672	71.9	12.1	6.8	8,722	–	–
	Sub-Saharan Africa	0.568	62.5	10.3	6.2	4,352	–	–
Least developed countries		0.560	66.5	10.2	5.1	3,637	–	–
Small island developing states		0.739	71.9	12.6	8.6	19,343	–	–
Organisation for Economic Co-operation and Development		0.916	80.6	16.5	12.3	52,698	–	–
World		**0.756**	**73.4**	**13.0**	**8.8**	**20,327**	**–**	**–**

Notes

a	Data refer to 2023 or the most recent year available.
b	Based on countries for which a Human Development Index (HDI) value is calculated.
c	In calculating the HDI value, expected years of schooling is capped at 18 years.
d	Updated by HDRO based on data from Barro and Lee (2018) and UNESCO Institute for Statistics (2024).
e	Updated by HDRO based on data from UNESCO Institute for Statistics (2024).
f	In calculating the HDI value, GNI per capita is capped at $75,000.
g	In calculating the HDI value, life expectancy is capped at 85 years.
h	Updated by HDRO using the mean years of schooling trend of Austria and data from UNESCO Institute for Statistics (2024).
i	Estimated using the purchasing power parity (PPP) rate and projected growth rate of Switzerland.
j	Updated by HDRO based on data from Eurostat (2024) and UNESCO Institute for Statistics (2024).
k	Refers to 2015 based on UNESCO Institute for Statistics (2024).
l	HDRO estimate based on data from Robert Barro and Jong-Wha Lee, ICF Macro Demographic and Health Surveys, the Organisation for Economic Co-operation and Development, United Nations Children's Fund (UNICEF) Multiple Indicator Cluster Surveys and the United Nations Educational, Scientific and Cultural Organization (UNESCO) Institute for Statistics.
m	Refers to 2020 based on UNESCO Institute for Statistics (2024).
n	HDRO estimate based on data from the Center for Distributive, Labor and Social Studies and the World Bank's Socio-Economic Database for Latin America and the Caribbean, ICF Macro Demographic and Health Surveys, the UNESCO Institute for Statistics and UNICEF Multiple Indicator Cluster Surveys.
o	Updated by HDRO based on data from UNICEF Multiple Indicator Cluster Surveys for various years and UNESCO Institute for Statistics (2024).
p	Updated by HDRO based on data from UNESCO Institute for Statistics (2024) and estimates using cross-country regression.
q	Based on HDRO estimates using cross-country regression.
r	HDRO estimate calculated based on United Nations Statistics Division (2025) and World Bank (2024a).
s	Refers to 2018 based on UNESCO Institute for Statistics (2024).
t	HDRO estimate based on data from IMF (2024) and World Bank (2024a).
u	IMF 2024.
v	Updated by HDRO based on data from UNICEF Multiple Indicator Cluster Surveys for various years.
w	HDRO estimate based on data from ICF Macro Demographic and Health Surveys, the UNESCO Institute for Statistics and UNICEF Multiple Indicator Cluster Surveys.
x	Updated by HDRO based on data from ICF Macro Demographic and Health Surveys for various years and UNESCO Institute for Statistics (2024).
y	Updated by HDRO based on data from UNICEF Multiple Indicator Cluster Surveys for various years and estimates using cross-country regression.
z	Refers to 2019 based on UNESCO Institute for Statistics (2024).
aa	HDRO estimate based on data from IMF (2024), United Nations Statistics Division (2025) and World Bank (2024a).
ab	Updated by HDRO based on data from ICF Macro Demographic and Health Surveys for various years.
ac	Refers to 2017 based on UNESCO Institute for Statistics (2024).
ad	Refers to 2008 based on UNESCO Institute for Statistics (2024).

Definitions

Human Development Index (HDI): A composite index measuring average achievement in three basic dimensions of human development—a long and healthy life, knowledge and a decent standard of living. See *Technical note 1* at https://hdr.undp.org/sites/default/files/2025_HDR/hdr2025_technical_notes.pdf for details on how the HDI is calculated.

Life expectancy at birth: Number of years a newborn infant could expect to live if prevailing patterns of age-specific mortality rates at the time of birth stay the same throughout the infant's life.

Expected years of schooling: Number of years of schooling that a child of school entrance age can expect to receive if prevailing patterns of age-specific enrolment rates persist throughout the child's life.

Mean years of schooling: Average number of years of education received by people ages 25 and older, converted from education attainment levels using official durations of each level.

Gross national income (GNI) per capita: Aggregate income of an economy generated by its production and its ownership of factors of production, less the incomes paid for the use of factors of production owned by the rest of the world, converted to international dollars using PPP rates, divided by midyear population.

GNI per capita rank minus HDI rank: Difference in ranking by GNI per capita and by HDI value. A negative value means that the country is better ranked by GNI than by HDI value.

HDI rank for 2022: Ranking by HDI value for 2022, calculated using the same most recently revised data available that were used to calculate HDI values for 2023.

Main data sources

Columns 1 and 7: HDRO calculations based on data from Barro and Lee (2018), IMF (2024), UNDESA (2024a), UNESCO Institute for Statistics (2024), United Nations Statistics Division (2025) and World Bank (2024a).

Column 2: UNDESA 2024a.

Column 3: ICF Macro Demographic and Health Surveys, UNESCO Institute for Statistics 2024 and UNICEF Multiple Indicator Cluster Surveys.

Column 4: Barro and Lee 2018, Eurostat 2024, ICF Macro Demographic and Health Surveys, UNESCO Institute for Statistics 2024 and UNICEF Multiple Indicator Cluster Surveys.

Column 5: IMF 2024, United Nations Statistics Division 2025 and World Bank 2024a.

Column 6: Calculated based on data in columns 1 and 5.

TABLE 2

Human Development Index trends, 1990–2023

HDI RANK		Human Development Index (HDI) Value								Change in HDI rank	Average annual HDI growth (%)			
		1990	2000	2010	2015	2020	2021	2022	2023	2015–2023[a]	1990–2000	2000–2010	2010–2023	1990–2023
Very high human development														
1	Iceland	0.841	0.902	0.935	0.956	0.965	0.967	0.964	0.972	2	0.70	0.36	0.30	0.44
2	Norway	0.856	0.924	0.947	0.959	0.969	0.969	0.967	0.970	-1	0.77	0.25	0.18	0.38
2	Switzerland	0.858	0.892	0.945	0.957	0.963	0.968	0.966	0.970	0	0.39	0.58	0.20	0.37
4	Denmark	0.844	0.896	0.920	0.943	0.954	0.958	0.959	0.962	2	0.60	0.26	0.34	0.40
5	Germany	0.834	0.897	0.936	0.948	0.955	0.958	0.955	0.959	-1	0.73	0.43	0.19	0.42
5	Sweden	0.818	0.912	0.918	0.945	0.951	0.958	0.959	0.959	0	1.09	0.07	0.34	0.48
7	Australia	0.867	0.897	0.929	0.938	0.950	0.954	0.952	0.958	1	0.34	0.35	0.24	0.30
8	Hong Kong, China (SAR)	0.755	0.839	0.912	0.937	0.950	0.961	0.950	0.955	2	1.06	0.84	0.36	0.71
8	Netherlands	0.855	0.900	0.925	0.940	0.945	0.951	0.953	0.955	-1	0.51	0.27	0.25	0.34
10	Belgium	0.824	0.894	0.921	0.933	0.939	0.948	0.945	0.951	3	0.82	0.30	0.25	0.44
11	Ireland	0.776	0.869	0.915	0.931	0.948	0.946	0.947	0.949	4	1.14	0.52	0.28	0.61
12	Finland	0.823	0.898	0.920	0.938	0.947	0.949	0.946	0.948	-4	0.88	0.24	0.23	0.43
13	Singapore	0.819	0.882	0.932	0.935	0.944	0.948	0.942	0.946	-2	0.74	0.55	0.11	0.44
13	United Kingdom	0.812	0.870	0.921	0.931	0.930	0.941	0.946	0.946	2	0.69	0.57	0.21	0.46
15	United Arab Emirates	0.713	0.790	0.835	0.857	0.909	0.903	0.921	0.940	27	1.03	0.56	0.92	0.84
16	Canada	0.865	0.894	0.918	0.932	0.931	0.937	0.935	0.939	-2	0.33	0.27	0.17	0.25
17	Liechtenstein	..	0.882	0.914	0.925	0.929	0.933	0.936	0.938	1	..	0.36	0.20	..
17	New Zealand	0.811	0.896	0.926	0.934	0.940	0.939	0.933	0.938	-5	1.00	0.33	0.10	0.44
17	United States	0.878	0.895	0.919	0.928	0.925	0.921	0.930	0.938	0	0.19	0.26	0.16	0.20
20	Korea (Republic of)	0.738	0.830	0.894	0.914	0.928	0.933	0.928	0.937	1	1.18	0.75	0.36	0.73
21	Slovenia	0.734	0.829	0.896	0.909	0.918	0.924	0.926	0.931	2	1.22	0.78	0.30	0.72
22	Austria	0.832	0.879	0.912	0.919	0.925	0.930	0.927	0.930	-3	0.55	0.37	0.15	0.34
23	Japan	0.853	0.889	0.907	0.917	0.922	0.922	0.921	0.925	-3	0.41	0.20	0.15	0.25
24	Malta	0.735	0.790	0.867	0.892	0.903	0.914	0.917	0.924	5	0.72	0.93	0.49	0.70
25	Luxembourg	0.787	0.861	0.909	0.913	0.916	0.918	0.922	0.922	-3	0.90	0.54	0.11	0.48
26	France	0.798	0.852	0.888	0.901	0.909	0.915	0.916	0.920	-1	0.66	0.41	0.27	0.43
27	Israel	0.787	0.839	0.889	0.902	0.912	0.918	0.921	0.919	-3	0.64	0.58	0.26	0.47
28	Spain	0.766	0.833	0.875	0.895	0.901	0.912	0.911	0.918	0	0.84	0.49	0.37	0.55
29	Czechia	0.753	0.817	0.880	0.900	0.898	0.901	0.911	0.915	-3	0.82	0.75	0.30	0.59
29	Italy	0.787	0.849	0.887	0.889	0.899	0.908	0.905	0.915	1	0.76	0.44	0.24	0.46
29	San Marino	..	0.881	0.905	0.896	0.895	0.903	0.910	0.915	-2	..	0.27	0.08	..
32	Andorra	..	0.825	0.870	0.869	0.851	0.871	0.893	0.913	3	..	0.53	0.37	..
32	Cyprus	0.749	0.808	0.869	0.882	0.905	0.907	0.908	0.913	1	0.76	0.73	0.38	0.60
34	Greece	0.770	0.828	0.876	0.888	0.896	0.897	0.897	0.908	-3	0.73	0.57	0.28	0.50
35	Poland	0.722	0.801	0.852	0.879	0.880	0.884	0.902	0.906	-1	1.04	0.62	0.47	0.69
36	Estonia	0.738	0.793	0.868	0.888	0.901	0.899	0.902	0.905	-5	0.72	0.91	0.32	0.62
37	Saudi Arabia	0.670	0.737	0.801	0.851	0.875	0.878	0.893	0.900	9	0.96	0.84	0.90	0.90
38	Bahrain	0.734	0.775	0.810	0.868	0.885	0.885	0.902	0.899	-1	0.55	0.44	0.81	0.62
39	Lithuania	0.745	0.778	0.854	0.869	0.888	0.887	0.888	0.895	-4	0.43	0.94	0.36	0.56
40	Portugal	0.707	0.797	0.836	0.857	0.870	0.876	0.883	0.890	2	1.21	0.48	0.48	0.70
41	Croatia	..	0.769	0.831	0.852	0.867	0.876	0.886	0.889	4	..	0.78	0.52	..
41	Latvia	0.736	0.764	0.833	0.859	0.879	0.871	0.881	0.889	-1	0.37	0.87	0.50	0.57
43	Qatar	0.767	0.795	0.834	0.860	0.872	0.866	0.883	0.886	-4	0.36	0.48	0.47	0.44
44	Slovakia	0.698	0.774	0.851	0.861	0.867	0.859	0.873	0.880	-6	1.04	0.95	0.26	0.70
45	Chile	0.718	0.771	0.823	0.855	0.856	0.865	0.869	0.878	-1	0.71	0.65	0.50	0.61
46	Hungary	0.730	0.781	0.838	0.847	0.857	0.852	0.867	0.870	1	0.68	0.71	0.29	0.53
47	Argentina	0.733	0.789	0.844	0.859	0.851	0.847	0.858	0.865	-7	0.74	0.68	0.19	0.50
48	Montenegro	..	..	0.815	0.839	0.841	0.840	0.853	0.862	0	..	..	0.43	..
48	Uruguay	0.713	0.764	0.796	0.818	0.837	0.837	0.852	0.862	13	0.69	0.41	0.61	0.58
50	Oman	..	0.707	0.804	0.838	0.843	0.834	0.846	0.858	1	..	1.29	0.50	..
51	Türkiye	0.598	0.669	0.750	0.821	0.838	0.841	0.853	0.853	7	1.13	1.15	0.99	1.08
52	Kuwait	0.698	0.778	0.812	0.832	0.837	0.839	0.845	0.852	1	1.09	0.43	0.37	0.61
53	Antigua and Barbuda	..	..	0.828	0.839	0.840	0.843	0.848	0.851	-5	..	..	0.21	..
54	Seychelles	..	..	0.758	0.819	0.853	0.838	0.836	0.848	5	..	..	0.87	..
55	Bulgaria	0.706	0.733	0.799	0.824	0.826	0.817	0.835	0.845	1	0.38	0.87	0.43	0.55
55	Romania	0.719	0.730	0.822	0.823	0.832	0.829	0.840	0.845	2	0.15	1.19	0.21	0.49
57	Georgia	..	0.705	0.770	0.807	0.822	0.819	0.838	0.844	6	..	0.89	0.71	..
58	Saint Kitts and Nevis	..	..	0.791	0.830	0.828	0.818	0.829	0.840	-4	..	..	0.46	..
59	Panama	0.672	0.718	0.775	0.803	0.808	0.819	0.835	0.839	6	0.66	0.77	0.61	0.67
60	Brunei Darussalam	0.781	0.792	0.830	0.839	0.836	0.835	0.825	0.837	-12	0.14	0.47	0.06	0.21
60	Kazakhstan	0.689	0.692	0.781	0.819	0.826	0.816	0.831	0.837	-1	0.04	1.22	0.53	0.59
62	Costa Rica	0.677	0.720	0.776	0.803	0.819	0.817	0.823	0.833	3	0.62	0.75	0.55	0.63

Continued →

HDI RANK		Human Development Index (HDI) Value								Change in HDI rank	Average annual HDI growth (%)			
		1990	2000	2010	2015	2020	2021	2022	2023	2015-2023[a]	1990-2000	2000-2010	2010-2023	1990-2023
62	Serbia	..	0.701	0.775	0.802	0.809	0.807	0.826	0.833	5	..	1.01	0.56	..
64	Russian Federation	0.762	0.750	0.808	0.833	0.818	0.813	0.826	0.832	-12	-0.16	0.75	0.23	0.27
65	Belarus	..	0.724	0.803	0.825	0.815	0.817	0.824	0.824	-10	..	1.04	0.20	..
66	Bahamas	0.762	0.787	0.801	0.807	0.797	0.794	0.818	0.820	-3	0.32	0.18	0.18	0.22
67	Malaysia	0.653	0.733	0.779	0.800	0.810	0.802	0.810	0.819	2	1.16	0.61	0.39	0.69
68	North Macedonia	0.644	0.686	0.765	0.795	0.783	0.781	0.811	0.815	4	0.63	1.10	0.49	0.72
69	Armenia	0.663	0.667	0.747	0.777	0.761	0.786	0.801	0.811	9	0.06	1.14	0.63	0.61
69	Barbados	0.730	0.762	0.797	0.800	0.803	0.803	0.807	0.811	0	0.43	0.45	0.13	0.32
71	Albania	0.654	0.682	0.769	0.797	0.794	0.794	0.806	0.810	0	0.42	1.21	0.40	0.65
72	Trinidad and Tobago	0.661	0.714	0.789	0.808	0.800	0.796	0.805	0.807	-10	0.77	1.00	0.17	0.61
73	Mauritius	0.627	0.683	0.755	0.792	0.795	0.789	0.794	0.806	0	0.86	1.01	0.50	0.76
74	Bosnia and Herzegovina	..	0.674	0.725	0.769	0.783	0.783	0.799	0.804	7	..	0.73	0.80	..
High human development														
75	Iran (Islamic Republic of)	0.626	0.710	0.778	0.788	0.775	0.777	0.793	0.799	-1	1.27	0.92	0.21	0.74
76	Saint Vincent and the Grenadines	..	0.700	0.746	0.765	0.781	0.781	0.794	0.798	11	..	0.64	0.52	..
76	Thailand	0.584	0.657	0.742	0.788	0.798	0.800	0.792	0.798	-2	1.18	1.22	0.56	0.95
78	China	0.491	0.598	0.710	0.750	0.786	0.794	0.796	0.797	16	1.99	1.73	0.89	1.48
79	Peru	0.625	0.682	0.731	0.768	0.769	0.764	0.790	0.794	5	0.88	0.70	0.64	0.73
80	Grenada	..	..	0.771	0.782	0.782	0.782	0.789	0.791	-4	..	..	0.20	..
81	Azerbaijan	..	0.652	0.744	0.771	0.757	0.765	0.784	0.789	-1	..	1.33	0.45	..
81	Mexico	0.668	0.712	0.751	0.773	0.763	0.761	0.783	0.789	-2	0.64	0.53	0.38	0.51
83	Colombia	0.623	0.679	0.741	0.767	0.764	0.762	0.782	0.788	3	0.86	0.88	0.47	0.71
84	Brazil	0.641	0.690	0.748	0.764	0.770	0.768	0.780	0.786	4	0.74	0.81	0.38	0.62
84	Palau	..	0.736	0.779	0.802	0.799	0.789	0.786	0.786	-17	..	0.57	0.07	..
86	Moldova (Republic of)	..	..	0.739	0.759	0.770	0.773	0.784	0.785	5	..	..	0.47	..
87	Ukraine	0.750	0.716	0.782	0.778	0.783	0.772	0.772	0.779	-10	-0.46	0.89	-0.03	0.12
88	Ecuador	0.646	0.683	0.737	0.764	0.740	0.753	0.773	0.777	0	0.56	0.76	0.41	0.56
89	Dominican Republic	0.589	0.658	0.715	0.747	0.767	0.762	0.778	0.776	6	1.11	0.83	0.63	0.84
89	Guyana	0.494	0.567	0.647	0.683	0.722	0.713	0.763	0.776	33	1.39	1.33	1.41	1.38
89	Sri Lanka	0.638	0.702	0.748	0.769	0.780	0.777	0.777	0.776	-8	0.96	0.64	0.28	0.60
92	Tonga	0.641	0.688	0.724	0.743	0.765	0.763	0.764	0.769	4	0.71	0.51	0.46	0.55
93	Maldives	..	0.639	0.689	0.725	0.730	0.745	0.764	0.766	10	..	0.76	0.82	..
93	Viet Nam	0.499	0.604	0.686	0.717	0.755	0.754	0.764	0.766	16	1.93	1.28	0.85	1.31
95	Turkmenistan	..	..	0.700	0.725	0.744	0.754	0.761	0.764	8	..	..	0.68	..
96	Algeria	0.595	0.651	0.718	0.737	0.742	0.755	0.761	0.763	3	0.90	0.98	0.47	0.76
97	Cuba	0.687	0.697	0.783	0.769	0.762	0.745	0.764	0.762	-16	0.14	1.17	-0.21	0.31
98	Dominica	..	0.721	0.747	0.741	0.753	0.749	0.759	0.761	0	..	0.35	0.14	..
99	Paraguay	0.607	0.664	0.709	0.737	0.742	0.723	0.747	0.756	0	0.90	0.66	0.49	0.67
100	Egypt	0.572	0.639	0.677	0.706	0.736	0.738	0.751	0.754	15	1.11	0.58	0.83	0.84
100	Jordan	0.619	0.672	0.732	0.743	0.743	0.736	0.751	0.754	-4	0.82	0.86	0.23	0.60
102	Lebanon	..	..	0.750	0.763	0.750	0.733	0.755	0.752	-12	..	..	0.02	..
103	Saint Lucia	0.683	0.710	0.749	0.757	0.734	0.724	0.747	0.748	-11	0.39	0.54	-0.01	0.28
104	Mongolia	0.593	0.611	0.714	0.753	0.741	0.727	0.742	0.747	-11	0.30	1.57	0.35	0.70
105	Tunisia	0.569	0.654	0.717	0.728	0.733	0.728	0.745	0.746	-4	1.40	0.92	0.31	0.82
106	South Africa	0.633	0.618	0.669	0.722	0.724	0.721	0.737	0.741	-1	-0.24	0.80	0.79	0.48
107	Uzbekistan	..	0.603	0.681	0.707	0.723	0.727	0.737	0.740	7	..	1.22	0.64	..
108	Bolivia (Plurinational State of)	0.552	0.630	0.677	0.704	0.697	0.693	0.727	0.733	8	1.33	0.72	0.61	0.86
108	Gabon	0.621	0.652	0.684	0.720	0.732	0.720	0.730	0.733	-1	0.49	0.48	0.53	0.50
108	Marshall Islands	..	..	..	0.691	0.722	0.723	0.732	0.733	11	..	..	..	..
111	Botswana	0.590	0.594	0.652	0.690	0.718	0.700	0.729	0.731	9	0.07	0.94	0.88	0.65
111	Fiji	0.629	0.668	0.697	0.715	0.718	0.705	0.726	0.731	-1	0.60	0.43	0.37	0.46
113	Indonesia	0.531	0.600	0.670	0.701	0.710	0.707	0.726	0.728	4	1.23	1.11	0.64	0.96
114	Suriname	..	..	0.707	0.718	0.714	0.697	0.719	0.722	-6	..	..	0.16	..
115	Belize	0.617	0.671	0.727	0.721	0.713	0.713	0.717	0.721	-9	0.84	0.80	-0.06	0.47
115	Libya	0.690	0.727	0.755	0.728	0.688	0.729	0.741	0.721	-14	0.52	0.38	-0.35	0.13
117	Jamaica	0.662	0.659	0.708	0.713	0.711	0.703	0.718	0.720	-6	-0.05	0.72	0.13	0.25
117	Kyrgyzstan	0.649	0.627	0.668	0.695	0.700	0.704	0.717	0.720	1	-0.34	0.64	0.58	0.32
117	Philippines	0.593	0.632	0.669	0.690	0.699	0.690	0.714	0.720	3	0.64	0.57	0.57	0.59
120	Morocco	0.451	0.528	0.607	0.659	0.683	0.690	0.704	0.710	7	1.59	1.40	1.21	1.38
121	Venezuela (Bolivarian Republic of)	0.658	0.703	0.764	0.768	0.699	0.696	0.706	0.709	-37	0.66	0.84	-0.57	0.23
122	Samoa	..	0.676	0.708	0.708	0.708	0.706	0.703	0.708	-9	..	0.46	0.00	..
123	Nicaragua	0.515	0.593	0.651	0.679	0.676	0.682	0.701	0.706	0	1.42	0.94	0.63	0.96
124	Nauru	..	..	0.616	0.660	0.684	0.692	0.700	0.703	2	..	..	1.02	..

Continued →

HDI RANK		Human Development Index (HDI)								Change in HDI rank	Average annual HDI growth			
		Value									(%)			
		1990	2000	2010	2015	2020	2021	2022	2023	2015-2023[a]	1990-2000	2000-2010	2010-2023	1990-2023
Medium human development														
125	Bhutan	..	..	0.593	0.637	0.688	0.691	0.695	0.698	9	..	..	1.26	..
126	Eswatini (Kingdom of)	0.570	0.493	0.534	0.607	0.657	0.658	0.695	0.695	16	-1.44	0.80	2.05	0.60
126	Iraq	0.531	0.592	0.650	0.675	0.680	0.687	0.695	0.695	-2	1.09	0.94	0.52	0.82
128	Tajikistan	..	0.554	0.639	0.658	0.664	0.672	0.687	0.691	0	..	1.44	0.60	..
129	Tuvalu	0.566	0.610	0.636	0.658	0.681	0.681	0.686	0.689	-1	0.75	0.42	0.62	0.60
130	Bangladesh	0.397	0.477	0.561	0.621	0.663	0.663	0.680	0.685	9	1.85	1.64	1.55	1.67
130	India	0.446	0.501	0.590	0.633	0.652	0.647	0.676	0.685	5	1.17	1.65	1.16	1.31
132	El Salvador	0.523	0.607	0.660	0.667	0.660	0.663	0.674	0.678	-7	1.50	0.84	0.21	0.79
133	Equatorial Guinea	..	0.508	0.612	0.656	0.668	0.671	0.677	0.674	-2	..	1.88	0.75	..
133	Palestine, State of	..	..	0.691	0.712	0.718	0.718	0.733	0.674	-21	..	..	-0.19	..
135	Cabo Verde	..	0.585	0.648	0.658	0.647	0.651	0.664	0.668	-7	..	1.03	0.23	..
136	Namibia	0.597	0.561	0.591	0.630	0.647	0.631	0.649	0.665	0	-0.62	0.52	0.91	0.33
137	Guatemala	0.499	0.563	0.623	0.638	0.645	0.639	0.655	0.662	-4	1.21	1.02	0.47	0.86
138	Congo	0.573	0.545	0.609	0.643	0.643	0.643	0.644	0.649	-6	-0.50	1.12	0.49	0.38
139	Honduras	0.516	0.558	0.596	0.610	0.625	0.628	0.643	0.645	1	0.79	0.66	0.61	0.68
140	Kiribati	..	..	0.600	0.623	0.632	0.631	0.642	0.644	-2	..	..	0.55	..
141	Sao Tome and Principe	..	..	0.564	0.608	0.628	0.631	0.636	0.637	0	..	..	0.94	..
142	Timor-Leste	..	0.507	0.645	0.628	0.650	0.644	0.633	0.634	-5	..	2.44	-0.13	..
143	Ghana	0.432	0.487	0.558	0.588	0.614	0.618	0.625	0.628	4	1.21	1.37	0.91	1.14
143	Kenya	0.485	0.500	0.552	0.583	0.600	0.608	0.626	0.628	5	0.31	0.99	1.00	0.79
145	Nepal	0.404	0.471	0.551	0.575	0.599	0.596	0.605	0.622	5	1.55	1.58	0.94	1.32
146	Vanuatu	..	..	0.582	0.599	0.617	0.615	0.621	0.621	0	..	..	0.50	..
147	Lao People's Democratic Republic	0.409	0.473	0.556	0.604	0.616	0.613	0.614	0.617	-4	1.46	1.63	0.80	1.25
148	Angola	..	0.391	0.528	0.603	0.610	0.609	0.615	0.616	-3	..	3.05	1.19	..
149	Micronesia (Federated States of)	..	0.596	0.603	0.604	0.609	0.611	0.614	0.615	-6	..	0.12	0.15	..
150	Myanmar	0.347	0.415	0.515	0.566	0.609	0.605	0.606	0.609	3	1.81	2.18	1.30	1.72
151	Cambodia	0.387	0.438	0.543	0.562	0.595	0.594	0.602	0.606	5	1.25	2.17	0.85	1.37
152	Comoros	..	0.461	0.534	0.565	0.592	0.594	0.602	0.603	2	..	1.48	0.94	..
153	Zimbabwe	0.500	0.458	0.512	0.567	0.582	0.581	0.594	0.598	-1	-0.87	1.12	1.20	0.54
154	Zambia	0.422	0.429	0.533	0.565	0.578	0.574	0.589	0.595	0	0.16	2.19	0.85	1.05
155	Cameroon	0.448	0.439	0.529	0.575	0.579	0.574	0.581	0.588	-5	-0.20	1.88	0.82	0.83
156	Solomon Islands	..	0.547	0.564	0.576	0.579	0.577	0.583	0.584	-7	..	0.31	0.27	..
157	Côte d'Ivoire	0.389	0.419	0.465	0.519	0.553	0.557	0.565	0.582	10	0.75	1.05	1.74	1.23
157	Uganda	0.342	0.407	0.514	0.547	0.571	0.573	0.578	0.582	3	1.76	2.36	0.96	1.62
159	Rwanda	..	0.340	0.504	0.525	0.555	0.562	0.570	0.578	5	..	4.01	1.06	..
160	Papua New Guinea	0.403	0.456	0.503	0.543	0.567	0.567	0.572	0.576	1	1.24	0.99	1.05	1.09
161	Togo	0.412	0.448	0.483	0.523	0.554	0.560	0.567	0.571	4	0.84	0.76	1.30	0.99
162	Syrian Arab Republic	0.572	0.594	0.669	0.549	0.570	0.571	0.571	0.564	-3	0.38	1.20	-1.30	-0.04
163	Mauritania	0.396	0.468	0.525	0.551	0.554	0.553	0.562	0.563	-5	1.68	1.16	0.54	1.07
164	Nigeria	0.379	0.435	0.502	0.530	0.547	0.554	0.557	0.560	-2	1.39	1.44	0.84	1.19
165	Tanzania (United Republic of)	0.381	0.414	0.513	0.520	0.554	0.548	0.554	0.555	1	0.83	2.17	0.61	1.15
166	Haiti	0.461	0.497	0.452	0.552	0.555	0.548	0.552	0.554	-9	0.75	-0.94	1.58	0.56
167	Lesotho	0.483	0.462	0.478	0.517	0.537	0.532	0.547	0.550	1	-0.44	0.34	1.09	0.39
Low human development														
168	Pakistan	0.396	0.436	0.500	0.527	0.536	0.537	0.544	0.544	-5	0.97	1.38	0.65	0.97
169	Senegal	0.377	0.398	0.477	0.509	0.522	0.522	0.526	0.530	1	0.54	1.83	0.81	1.04
170	Gambia	0.331	0.403	0.463	0.482	0.512	0.513	0.519	0.524	5	1.99	1.40	0.96	1.40
171	Congo (Democratic Republic of the)	0.388	0.391	0.440	0.477	0.506	0.508	0.514	0.522	8	0.08	1.19	1.32	0.90
172	Malawi	0.306	0.394	0.475	0.504	0.512	0.509	0.513	0.517	-1	2.56	1.89	0.65	1.60
173	Benin	0.351	0.415	0.485	0.511	0.504	0.506	0.512	0.515	-4	1.69	1.57	0.46	1.17
174	Guinea-Bissau	..	..	0.452	0.481	0.498	0.502	0.511	0.514	2	..	..	0.99	..
175	Djibouti	..	0.337	0.421	0.469	0.499	0.501	0.510	0.513	6	..	2.25	1.53	..
176	Sudan	..	..	0.479	0.498	0.513	0.512	0.516	0.511	-3	..	..	0.50	..
177	Liberia	..	0.443	0.467	0.480	0.498	0.503	0.508	0.510	0	..	0.53	0.68	..
178	Eritrea	..	..	0.465	0.480	0.495	0.496	0.499	0.503	-1	..	..	0.61	..
179	Guinea	0.282	0.359	0.430	0.465	0.488	0.490	0.498	0.500	3	2.44	1.82	1.17	1.75
180	Ethiopia	..	0.293	0.415	0.456	0.486	0.487	0.494	0.497	4	..	3.54	1.40	..
181	Afghanistan	0.285	0.351	0.465	0.496	0.501	0.486	0.495	0.496	-7	2.10	2.85	0.50	1.69
182	Mozambique	0.246	0.311	0.419	0.457	0.477	0.478	0.490	0.493	1	2.37	3.03	1.26	2.13
183	Madagascar	..	0.443	0.493	0.501	0.483	0.481	0.483	0.487	-11	..	1.08	-0.09	..
184	Yemen	0.359	0.439	0.502	0.475	0.459	0.458	0.466	0.470	-4	2.03	1.35	-0.51	0.82
185	Sierra Leone	0.313	0.318	0.410	0.432	0.454	0.458	0.463	0.467	0	0.16	2.57	1.01	1.22

Continued →

HDI RANK		Human Development Index (HDI) Value								Change in HDI rank	Average annual HDI growth (%)			
		1990	2000	2010	2015	2020	2021	2022	2023	2015–2023[a]	1990–2000	2000–2010	2010–2023	1990–2023
186	Burkina Faso	..	..	0.377	0.419	0.453	0.454	0.457	0.459	1	..	..	1.53	..
187	Burundi	0.294	0.308	0.416	0.432	0.435	0.435	0.437	0.439	-2	0.47	3.05	0.41	1.22
188	Mali	0.240	0.320	0.410	0.413	0.414	0.414	0.417	0.419	0	2.92	2.51	0.17	1.70
188	Niger	0.215	0.266	0.339	0.374	0.404	0.413	0.414	0.419	3	2.15	2.45	1.64	2.04
190	Chad	..	0.303	0.375	0.396	0.408	0.408	0.414	0.416	-1	..	2.15	0.80	..
191	Central African Republic	0.342	0.333	0.358	0.377	0.386	0.339	..	0.414	-1	-0.27	0.73	1.12	0.58
192	Somalia	..	..	..	..	..	..	0.385	0.404	..	..	..	..	..
193	South Sudan	..	..	0.420	0.317	0.398	0.393	0.388	0.388	0	..	..	-0.61	..
Other countries or territories														
	Korea (Democratic People's Rep. of)	..	..	..	..	..	..	..	..	..	..	..	..	..
	Monaco	..	..	..	..	..	..	..	..	..	..	..	..	..
Human development groups														
	Very high human development	0.797	0.838	0.879	0.898	0.901	0.903	0.908	0.914	—	0.50	0.48	0.30	0.42
	High human development	0.569	0.636	0.714	0.744	0.763	0.766	0.774	0.777	—	1.12	1.16	0.65	0.95
	Medium human development	0.439	0.491	0.573	0.611	0.631	0.629	0.649	0.656	—	1.13	1.56	1.05	1.22
	Low human development	0.346	0.393	0.467	0.491	0.507	0.507	0.512	0.515	—	1.28	1.74	0.76	1.21
Developing countries		0.520	0.576	0.649	0.680	0.696	0.696	0.708	0.712	—	1.03	1.20	0.72	0.96
Regions														
	Arab States	0.550	0.615	0.670	0.693	0.707	0.710	0.716	0.719	—	1.12	0.86	0.54	0.82
	East Asia and the Pacific	0.514	0.604	0.699	0.735	0.764	0.768	0.773	0.775	—	1.63	1.47	0.80	1.25
	Europe and Central Asia	0.674	0.686	0.753	0.789	0.802	0.803	0.815	0.818	—	0.18	0.94	0.64	0.59
	Latin America and the Caribbean	0.648	0.697	0.747	0.767	0.764	0.762	0.778	0.783	—	0.73	0.70	0.36	0.58
	South Asia	0.454	0.508	0.590	0.627	0.645	0.641	0.665	0.672	—	1.13	1.51	1.01	1.20
	Sub-Saharan Africa	0.405	0.435	0.510	0.540	0.557	0.558	0.565	0.568	—	0.72	1.60	0.83	1.03
Least developed countries		0.360	0.411	0.494	0.526	0.550	0.549	0.555	0.560	—	1.33	1.86	0.97	1.35
Small island developing states		0.617 [b]	0.660	0.702	0.727	0.731	0.727	0.737	0.739	—	0.68	0.62	0.40	0.55
Organisation for Economic Co-operation and Development		0.801	0.846	0.883	0.899	0.903	0.904	0.910	0.916	—	0.55	0.43	0.28	0.41
World		**0.608**	**0.651**	**0.707**	**0.731**	**0.742**	**0.742**	**0.752**	**0.756**	**—**	**0.69**	**0.83**	**0.52**	**0.66**

Notes

For HDI values that are comparable across years and countries, use this table or the interpolated data at https://hdr.undp.org/en/data, which present trends using consistent data.

a A positive value indicates an improvement in rank.

b Value reported with relaxed aggregation rule. For details, see *Reader's guide*.

Definitions

Human Development Index (HDI): A composite index measuring average achievement in three basic dimensions of human development—a long and healthy life, knowledge and a decent standard of living. See *Technical note 1* at https://hdr.undp.org/sites/default/files/2025_HDR/hdr2025_technical_notes.pdf for details on how the HDI is calculated.

Average annual HDI growth: A smoothed annualized growth of the HDI in a given period, calculated as the annual compound growth rate.

Main data sources

Columns 1–8: HDRO calculations based on data from Barro and Lee (2018), IMF (2024), UNDESA (2024a), UNESCO Institute for Statistics (2024), United Nations Statistics Division (2025) and World Bank (2024a).

Column 9: Calculated based on data in columns 4 and 8.

Columns 10–13: Calculated based on data in columns 1, 2, 3 and 8.

TABLE 3

Inequality-adjusted Human Development Index

HDI RANK		Human Development Index (HDI)	Inequality-adjusted HDI (IHDI)			Coefficient of human inequality	Inequality in life expectancy	Inequality-adjusted life expectancy index	Inequality in education[a]	Inequality-adjusted education index	Inequality in income	Inequality-adjusted income index	SDG 10.1 Income shares held by (%)			Gini coefficient
		Value	Value	Overall loss (%)	Difference from HDI rank[b]		(%)	Value	(%)	Value	(%)	Value	Poorest 40 percent	Richest 10 percent	Richest 1 percent	
		2023	2023	2023	2023	2023	2023[c]	2023	2023[d]	2023	2022[e]	2022	2010–2023[f]	2010–2023[f]	2023	2010–2023[f]
Very high human development																
1	Iceland	0.972	0.923	5.0	0	5.0	2.0	0.945	2.3	0.942	10.7	0.882	23.9	22.0	8.0	26.1
2	Norway	0.970	0.909	6.3	0	6.2	2.4	0.950	1.8	0.921	14.3	0.857	22.9	22.4	9.3	27.7
2	Switzerland	0.970	0.894	7.8	–2	7.5	3.1	0.953	1.8	0.912	17.7	0.823	19.7	26.4	9.8	33.7
4	Denmark	0.962	0.909	5.5	2	5.5	3.1	0.924	2.3	0.913	11.0	0.890	23.1	23.8	12.0	28.3
5	Germany	0.959	0.890	7.2	–3	7.1	3.2	0.914	3.7	0.922	14.3	0.836	20.6	25.0	12.8	32.4
5	Sweden	0.959	0.886	7.6	–4	7.4	2.6	0.948	2.6	0.901	16.9	0.815	21.5	22.7	10.9	29.8
7	Australia	0.958	0.873	8.9	–5	8.6	3.0	0.954	4.3	0.889	18.5	0.784	19.6	26.2	9.9	34.3
8	Hong Kong, China (SAR)	0.955	0.839	12.1	–16	11.7	2.3	0.977	8.7	0.805	24.1	0.750	..	..	17.9	..
8	Netherlands	0.955	0.892	6.6	3	6.4	3.3	0.925	4.7	0.879	11.4	0.874	24.0	21.4	6.8	25.7
10	Belgium	0.951	0.891	6.3	4	6.3	3.5	0.922	4.0	0.886	11.3	0.865	23.6	21.9	8.5	26.6
11	Ireland	0.949	0.886	6.6	2	6.5	3.1	0.930	2.6	0.868	14.0	0.860	22.0	24.8	13.6	30.1
12	Finland	0.948	0.891	6.0	6	5.9	2.9	0.925	2.0	0.914	12.8	0.836	23.2	22.9	11.1	27.7
13	Singapore	0.946	0.823	13.0	–19	12.4	2.6	0.955	8.7	0.790	25.9	0.741	..	..	14.2	..
13	United Kingdom	0.946	0.869	8.1	0	7.9	3.9	0.907	3.2	0.915	16.7	0.792	20.2	24.6	13.1	32.4
15	United Arab Emirates	0.940	0.866	7.9	–1	7.9	3.9	0.930	9.3	0.786	10.4	0.889	23.0	20.5	16.1	26.4
16	Canada	0.939	0.867	7.7	2	7.5	4.3	0.923	2.2	0.884	16.0	0.800	20.5	24.0	11.6	31.7
17	Liechtenstein	0.938	..	..	..	..	4.9	0.931	..	..	..	..	..	..	11.5	..
17	New Zealand	0.938	0.853	9.1	–2	8.8	4.4	0.913	4.1	0.892	18.1	0.762	..	..	12.1	..
17	United States	0.938	0.832	11.3	–12	10.7	5.5	0.862	2.7	0.882	23.9	0.759	15.6	30.2	20.7	41.3
20	Korea (Republic of)	0.937	0.857	8.5	1	8.4	2.5	0.965	6.2	0.831	16.4	0.784	19.9	24.6	15.1	32.9
21	Slovenia	0.931	0.885	4.9	9	4.9	2.6	0.923	2.0	0.899	10.0	0.834	24.9	20.6	8.0	24.3
22	Austria	0.930	0.861	7.4	4	7.1	3.2	0.923	2.6	0.842	15.6	0.823	21.0	23.8	11.5	30.7
23	Japan	0.925	0.845	8.6	2	8.5	2.5	0.970	5.8	0.805	17.1	0.772	20.8	26.1	12.7	32.9
24	Malta	0.924	0.843	8.8	2	8.6	5.2	0.923	5.2	0.812	15.5	0.799	21.0	25.1	9.0	31.4
25	Luxembourg	0.922	0.838	9.1	–1	8.9	4.8	0.911	5.4	0.774	16.4	0.836	19.5	24.5	13.1	32.7
26	France	0.920	0.836	9.1	–2	9.0	3.7	0.938	5.3	0.795	17.9	0.783	20.8	24.9	12.1	31.5
27	Israel	0.919	0.813	11.5	–11	11.0	3.6	0.926	5.3	0.820	24.0	0.709	16.6	26.6	16.8	37.9
28	Spain	0.918	0.819	10.8	–6	10.5	2.8	0.952	9.6	0.772	19.2	0.749	18.7	24.7	12.1	33.9
29	Czechia	0.915	0.867	5.2	14	5.1	3.0	0.893	1.2	0.888	11.1	0.823	24.1	22.2	9.7	26.2
29	Italy	0.915	0.817	10.7	–7	10.3	2.6	0.955	7.5	0.763	20.8	0.749	18.6	26.2	12.3	34.8
29	San Marino	0.915	..	..	..	..	1.8	0.982	4.1	0.752	..	..	..	..	11.5	..
32	Andorra	0.913	0.837	8.3	4	8.2	4.7	0.939	5.6	0.747	14.4	0.837	..	..	11.5	..
32	Cyprus	0.913	0.841	7.9	8	7.7	2.9	0.921	5.4	0.822	14.8	0.787	21.4	25.7	8.4	31.3
34	Greece	0.908	0.825	9.1	1	8.9	3.3	0.921	6.7	0.826	16.8	0.739	19.6	24.8	14.3	32.9
35	Poland	0.906	0.817	9.8	–2	9.5	3.9	0.867	4.8	0.861	19.8	0.732	22.4	22.8	15.2	28.5
36	Estonia	0.905	0.841	7.1	12	6.8	3.0	0.883	1.6	0.881	15.7	0.766	20.4	24.3	12.8	31.8
37	Saudi Arabia	0.900	..	..	..	..	5.1	0.857	12.8	0.748	..	..	..	..	25.2	..
38	Bahrain	0.899	..	..	..	..	4.7	0.898	13.2	0.706	..	..	..	..	25.5	..
39	Lithuania	0.895	0.812	9.3	–3	8.8	4.1	0.826	2.0	0.893	20.4	0.726	18.7	29.1	9.6	36.7
40	Portugal	0.890	0.795	10.7	–4	10.4	3.1	0.929	9.8	0.730	18.4	0.742	19.6	27.5	9.7	34.6
41	Croatia	0.889	0.828	6.9	7	6.7	3.6	0.869	3.0	0.832	13.5	0.787	21.8	22.3	9.0	28.9
41	Latvia	0.889	0.812	8.7	–1	8.3	4.2	0.828	1.7	0.889	19.0	0.727	19.2	26.2	10.7	34.3
43	Qatar	0.886	..	..	..	..	3.7	0.924	10.1	0.651	..	..	18.1	25.8	24.3	35.1
44	Slovakia	0.880	0.833	5.3	11	5.3	4.6	0.857	1.5	0.839	10.0	0.803	24.3	19.1	9.2	24.1
45	Chile	0.878	0.723	17.7	–16	16.1	4.6	0.898	6.0	0.795	37.7	0.530	15.8	34.5	22.0	43.0
46	Hungary	0.870	0.819	5.9	8	5.9	3.7	0.845	2.5	0.819	11.3	0.793	22.2	24.1	9.8	29.2
47	Argentina	0.865	0.761	12.0	–3	11.6	7.4	0.818	4.9	0.830	22.6	0.650	15.5	29.8	12.4	40.7
48	Montenegro	0.862	0.771	10.6	1	10.4	3.3	0.849	7.8	0.790	19.9	0.682	18.3	24.7	9.9	34.3
48	Uruguay	0.862	0.747	13.3	–10	12.9	5.9	0.842	7.6	0.773	25.1	0.640	15.9	30.5	14.8	40.6
50	Oman	0.858	0.750	12.6	–6	12.3	6.6	0.862	6.5	0.720	23.7	0.679	..	..	19.9	..
51	Türkiye	0.853	0.708	17.0	–14	16.5	8.1	0.808	12.4	0.700	28.9	0.628	14.7	34.7	24.4	44.4
52	Kuwait	0.852	..	..	..	..	5.8	0.876	22.1	0.541	..	..	..	..	17.6	..
53	Antigua and Barbuda	0.851	..	..	..	..	6.8	0.826	9.9	0.738	..	..	..	..	21.2	..
54	Seychelles	0.848	0.755	11.0	–2	10.8	9.3	0.738	6.7	0.815	16.6	0.715	19.7	23.9	20.5	32.1
55	Bulgaria	0.845	0.748	11.5	–4	11.0	4.9	0.814	4.3	0.772	23.7	0.665	17.1	29.9	16.9	39.0
55	Romania	0.845	0.758	10.3	2	9.8	4.9	0.818	3.7	0.746	20.9	0.714	18.4	24.0	13.4	33.9
57	Georgia	0.844	0.754	10.7	0	10.3	6.9	0.781	2.4	0.867	21.4	0.633	19.3	25.2	18.5	33.5

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HDI RANK		Human Development Index (HDI)	Inequality-adjusted HDI (IHDI)			Coefficient of human inequality	Inequality in life expectancy	Inequality-adjusted life expectancy index	Inequality in education[a]	Inequality-adjusted education index	Inequality in income	Inequality-adjusted income index	SDG 10.1 Income shares held by (%)			Gini coefficient
		Value	Value	Overall loss (%)	Difference from HDI rank[b]		(%)	Value	(%)	Value	(%)	Value	Poorest 40 percent	Richest 10 percent	Richest 1 percent	
		2023	2023	2023	2023	2023	2023[c]	2023	2023[d]	2023	2022[e]	2022	2010-2023[f]	2010-2023[f]	2023	2010-2023[f]
58	Saint Kitts and Nevis	0.840	..	..	..	..	9.9	0.723	..	..	..	..	..	..	21.2	..
59	Panama	0.839	0.664	20.9	-19	19.6	10.1	0.825	9.9	0.659	38.9	0.539	12.1	36.9	17.9	48.9
60	Brunei Darussalam	0.837	0.756	9.7	4	9.7	6.9	0.792	10.1	0.620	12.1	0.879	..	..	13.1	..
60	Kazakhstan	0.837	0.766	8.5	8	8.3	7.2	0.777	3.2	0.782	14.7	0.739	22.9	24.8	14.9	29.2
62	Costa Rica	0.833	0.678	18.6	-11	17.5	6.0	0.879	11.0	0.667	35.6	0.531	13.2	35.1	18.2	46.7
62	Serbia	0.833	0.772	7.3	13	7.3	4.2	0.836	4.1	0.773	13.5	0.712	20.0	25.9	12.5	33.1
64	Russian Federation	0.832	0.758	8.9	10	8.6	5.7	0.771	1.5	0.768	18.7	0.734	18.7	26.6	23.8	35.1
65	Belarus	0.824	0.771	6.4	15	6.3	3.5	0.808	2.8	0.770	12.7	0.737	24.8	20.7	9.6	24.4
66	Bahamas	0.820	0.670	18.3	-9	16.8	9.5	0.760	3.4	0.732	37.6	0.541	..	..	17.9	..
67	Malaysia	0.819	0.707	13.7	-2	13.3	6.1	0.819	9.0	0.657	24.8	0.658	16.1	30.9	14.9	40.7
68	North Macedonia	0.815	0.723	11.3	4	11.0	4.3	0.845	8.4	0.689	20.5	0.649	18.1	22.9	6.9	33.5
69	Armenia	0.811	0.743	8.4	7	8.3	6.7	0.799	2.9	0.755	15.1	0.681	22.8	23.0	15.0	27.9
69	Barbados	0.811	0.620	23.6	-22	20.6	7.2	0.802	5.5	0.749	49.0	0.397	..	..	21.2	..
71	Albania	0.810	0.705	13.0	1	12.8	6.4	0.859	12.3	0.651	19.7	0.627	21.6	22.8	8.9	29.4
72	Trinidad and Tobago	0.807	..	..	..	..	10.7	0.735	5.9	0.711	..	..	..	..	17.9	..
73	Mauritius	0.806	0.669	17.0	-5	16.2	9.8	0.762	7.4	0.676	31.4	0.581	18.8	29.9	15.9	36.8
74	Bosnia and Herzegovina	0.804	0.689	14.3	2	13.8	4.7	0.848	10.1	0.657	26.5	0.587	19.8	25.1	9.3	33.0
High human development																
75	Iran (Islamic Republic of)	0.799	0.643	19.5	-8	19.1	7.9	0.817	21.9	0.586	27.5	0.556	19.1	26.8	18.3	34.8
76	Saint Vincent and the Grenadines	0.798	..	..	..	..	10.3	0.707	6.1	0.778	..	..	..	..	21.2	..
76	Thailand	0.798	0.677	15.2	1	15.0	7.3	0.804	16.0	0.612	21.7	0.630	19.1	27.1	19.8	34.9
78	China	0.797	0.670	15.9	1	15.2	5.1	0.846	10.3	0.626	30.3	0.568	18.8	28.2	15.8	35.7
79	Peru	0.794	0.633	20.3	-10	19.9	9.7	0.802	19.3	0.608	30.6	0.520	16.2	30.7	26.9	40.3
80	Grenada	0.791	..	..	..	..	10.1	0.763	7.0	0.721	..	..	15.2	33.7	21.2	43.8
81	Azerbaijan	0.789	0.735	6.8	15	6.8	10.4	0.750	4.3	0.696	5.7	0.759	..	..	14.0	..
81	Mexico	0.789	0.646	18.1	-3	17.8	9.0	0.771	16.0	0.600	28.4	0.582	15.4	34.4	21.6	43.5
83	Colombia	0.788	0.593	24.7	-24	23.1	8.3	0.815	17.0	0.579	44.0	0.442	10.3	43.5	17.9	54.8
84	Brazil	0.786	0.594	24.4	-21	22.8	9.5	0.777	15.1	0.611	43.7	0.441	11.3	41.0	21.1	52.0
84	Palau	0.786	0.616	21.6	-11	20.1	13.6	0.655	5.8	0.786	40.9	0.453	..	..	16.1	..
86	Moldova (Republic of)	0.785	0.719	8.4	17	8.3	9.1	0.716	2.2	0.783	13.6	0.662	24.3	22.1	10.4	25.7
87	Ukraine	0.779	0.715	8.2	17	8.1	7.3	0.762	3.6	0.714	13.3	0.672	24.3	21.7	9.3	25.6
88	Ecuador	0.777	0.640	17.6	1	17.0	8.4	0.809	12.1	0.625	30.6	0.518	14.0	33.2	14.0	44.6
89	Dominican Republic	0.776	0.634	18.3	0	18.2	17.0	0.686	14.6	0.592	22.9	0.628	17.9	28.3	15.2	37.0
89	Guyana	0.776	..	..	..	..	14.9	0.657	10.4	0.584	..	..	..	..	17.9	..
89	Sri Lanka	0.776	0.630	18.8	-2	17.5	4.7	0.842	11.3	0.642	36.6	0.463	18.5	30.8	20.5	37.7
92	Tonga	0.769	0.682	11.3	16	11.0	7.9	0.749	4.3	0.821	20.7	0.516	23.1	22.0	16.1	27.1
93	Maldives	0.766	0.602	21.4	-7	20.5	3.7	0.904	29.3	0.425	28.6	0.568	22.1	23.3	13.1	29.3
93	Viet Nam	0.766	0.641	16.3	6	16.3	12.7	0.733	15.3	0.618	21.1	0.581	18.6	28.1	15.7	36.1
95	Turkmenistan	0.764	..	..	..	..	19.3	0.622	2.9	0.720	..	..	..	..	19.5	..
96	Algeria	0.763	0.601	21.2	-6	20.7	11.9	0.763	33.3	0.452	16.8	0.631	23.1	22.9	23.3	27.6
97	Cuba	0.762	..	..	..	..	4.8	0.851	9.1	0.673	..	..	..	..	13.7	..
98	Dominica	0.761	..	..	..	..	17.3	0.651	16.2	0.612	..	..	..	..	21.2	..
99	Paraguay	0.756	0.599	20.8	-6	20.0	10.6	0.740	14.7	0.585	34.6	0.497	14.5	35.4	17.9	45.1
100	Egypt	0.754	0.582	22.8	-13	22.0	10.4	0.711	36.9	0.443	18.7	0.625	21.8	27.5	19.1	31.9
100	Jordan	0.754	0.637	15.5	8	15.3	8.8	0.811	13.0	0.614	24.1	0.519	20.3	27.4	20.4	33.7
102	Lebanon	0.752	..	..	..	..	10.9	0.792	..	..	20.2	0.570	20.6	24.7	21.3	31.8
103	Saint Lucia	0.748	0.523	30.1	-20	29.1	10.6	0.725	37.4	0.401	39.2	0.491	15.1	34.1	21.2	43.7
104	Mongolia	0.747	0.647	13.4	16	13.3	8.8	0.726	11.9	0.610	19.2	0.610	20.8	24.6	16.1	31.4
105	Tunisia	0.746	0.595	20.2	-4	19.7	7.2	0.807	29.1	0.469	22.9	0.558	20.0	27.0	22.6	33.7
106	South Africa	0.741	0.476	35.8	-29	32.4	19.8	0.569	17.3	0.637	59.9	0.298	7.2	50.5	19.4	63.0
107	Uzbekistan	0.740	..	..	..	..	8.9	0.735	1.8	0.730	..	..	20.4	23.2	16.7	31.2
108	Bolivia (Plurinational State of)	0.733	0.578	21.1	-8	21.0	21.0	0.590	15.0	0.652	26.9	0.502	15.7	30.3	17.9	40.9
108	Gabon	0.733	0.558	23.9	-10	23.7	19.0	0.602	20.6	0.531	31.4	0.543	16.8	27.7	11.0	38.0
108	Marshall Islands	0.733	0.626	14.6	10	14.3	16.4	0.604	4.0	0.809	22.5	0.501	18.9	27.5	16.1	35.5
111	Botswana	0.731	0.509	30.4	-16	29.3	19.2	0.611	23.3	0.511	45.5	0.423	10.9	41.5	22.7	53.3
111	Fiji	0.731	0.626	14.4	13	14.2	15.5	0.615	8.6	0.667	18.5	0.598	21.3	24.2	16.1	30.7
113	Indonesia	0.728	0.608	16.5	10	16.4	12.5	0.688	12.9	0.575	23.6	0.568	19.5	29.9	17.9	36.1
114	Suriname	0.722	..	..	..	..	10.8	0.736	18.4	0.478	..	..	17.0	30.1	17.9	39.2

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HDI RANK		Human Development Index (HDI)	Inequality-adjusted HDI (IHDI)			Coefficient of human inequality	Inequality in life expectancy	Inequality-adjusted life expectancy index	Inequality in education[a]	Inequality-adjusted education index	Inequality in income	Inequality-adjusted income index	SDG 10.1 Income shares held by (%)			Gini coefficient
		Value	Value	Overall loss (%)	Difference from HDI rank[b]		(%)	Value	(%)	Value	(%)	Value	Poorest 40 percent	Richest 10 percent	Richest 1 percent	
		2023	2023	2023	2023	2023	2023[c]	2023	2023[d]	2023	2022[e]	2022	2010–2023[f]	2010–2023[f]	2023	2010–2023[f]
115	Belize	0.721	..	..	..	..	7.3	0.764	14.8	0.532	..	..	..	..	17.9	..
115	Libya	0.721	..	..	..	..	16.8	0.631	..	..	..	..	..	..	16.8	..
117	Jamaica	0.720	0.590	18.1	0	17.0	11.6	0.700	5.8	0.637	33.7	0.462	16.0	29.9	17.9	40.2
117	Kyrgyzstan	0.720	0.649	9.9	26	9.7	10.3	0.713	3.4	0.730	15.3	0.525	23.8	22.0	18.1	26.4
117	Philippines	0.720	0.597	17.1	5	16.8	15.0	0.652	12.0	0.606	23.6	0.540	16.9	32.5	16.6	40.7
120	Morocco	0.710	0.517	27.2	–9	26.1	10.6	0.761	41.9	0.364	25.9	0.499	17.4	31.9	13.4	39.5
121	Venezuela (Bolivarian Republic of)	0.709	0.605	14.7	14	14.5	12.6	0.706	9.7	0.616	21.1	0.509	..	..	17.9	..
122	Samoa	0.708	0.609	14.0	17	13.7	10.3	0.713	7.0	0.672	23.7	0.471	17.8	31.3	16.1	38.7
123	Nicaragua	0.706	0.535	24.2	–1	23.5	9.4	0.766	25.8	0.483	35.3	0.414	14.3	37.2	17.9	46.2
124	Nauru	0.703	0.599	14.8	14	14.7	16.8	0.539	8.7	0.613	18.5	0.650	20.5	25.3	16.1	32.4
Medium human development																
125	Bhutan	0.698	0.478	31.5	–10	30.0	13.1	0.708	48.2	0.290	28.6	0.532	22.3	22.7	14.0	28.5
126	Eswatini (Kingdom of)	0.695	0.431	38.0	–21	35.1	23.7	0.518	21.0	0.564	60.5	0.274	10.5	42.7	19.3	54.6
126	Iraq	0.695	0.534	23.2	0	22.8	13.3	0.698	29.7	0.400	25.5	0.545	21.9	23.7	15.7	29.5
128	Tajikistan	0.691	0.594	14.0	14	13.9	15.7	0.671	6.0	0.636	19.9	0.490	19.4	26.4	14.5	34.0
129	Tuvalu	0.689	0.578	16.1	10	15.8	13.1	0.630	9.2	0.638	25.1	0.480	17.4	30.8	16.1	39.1
130	Bangladesh	0.685	0.482	29.6	–3	29.0	15.8	0.709	35.3	0.368	35.9	0.430	20.4	27.4	16.2	33.4
130	India	0.685	0.475	30.7	–10	29.9	15.5	0.676	36.9	0.372	37.4	0.426	20.2	25.5	23.1	32.8
132	El Salvador	0.678	0.555	18.1	10	17.8	8.9	0.730	21.3	0.435	23.3	0.540	16.6	28.7	12.8	38.8
133	Equatorial Guinea	0.674	..	..	..	..	28.9	0.478	..	..	..	..	..	..	18.9	..
133	Palestine, State of	0.674	0.538	20.2	10	19.7	18.2	0.569	9.5	0.632	31.4	0.433	19.2	25.2	18.2	33.7
135	Cabo Verde	0.668	0.478	28.4	–1	26.8	7.6	0.797	27.4	0.377	45.4	0.363	15.4	32.3	13.9	42.4
136	Namibia	0.665	0.438	34.1	–10	32.4	19.2	0.589	25.0	0.427	53.0	0.333	8.6	47.2	21.6	59.1
137	Guatemala	0.662	0.479	27.6	2	26.9	13.0	0.704	35.0	0.320	32.8	0.490	13.1	38.0	17.9	48.3
138	Congo	0.649	0.426	34.4	–11	32.0	20.1	0.563	20.9	0.498	55.1	0.276	12.4	37.9	20.5	48.9
139	Honduras	0.645	0.496	23.1	7	22.4	9.9	0.733	21.6	0.418	35.6	0.400	11.6	34.6	17.9	48.2
140	Kiribati	0.644	0.535	16.9	15	16.6	24.7	0.538	9.6	0.573	15.5	0.498	23.0	22.8	16.1	27.8
141	Sao Tome and Principe	0.637	0.478	25.0	5	23.6	9.9	0.689	18.7	0.453	42.4	0.350	16.8	32.8	16.0	40.7
142	Timor-Leste	0.634	0.451	28.9	–2	27.7	22.2	0.571	44.9	0.317	16.1	0.507	22.8	24.0	15.2	28.7
143	Ghana	0.628	0.399	36.5	–10	35.4	22.1	0.545	33.0	0.371	51.0	0.313	14.3	32.2	15.2	43.5
143	Kenya	0.628	0.456	27.4	0	26.7	20.9	0.531	19.7	0.487	39.6	0.367	18.2	31.8	15.9	38.7
145	Nepal	0.622	0.437	29.7	–2	28.9	15.0	0.659	39.8	0.320	31.9	0.397	21.8	24.2	13.7	30.0
146	Vanuatu	0.621	0.521	16.1	17	16.0	11.1	0.704	17.9	0.466	19.1	0.431	20.0	24.7	16.1	32.3
147	Lao People's Democratic Republic	0.617	0.462	25.1	5	24.9	19.7	0.605	31.3	0.322	23.6	0.507	17.8	31.2	19.7	38.8
148	Angola	0.616	0.360	41.6	–15	39.9	27.4	0.498	34.2	0.353	58.1	0.266	11.5	39.6	26.0	51.3
149	Micronesia (Federated States of)	0.615	..	..	..	..	14.4	0.622	..	..	25.8	0.420	16.2	29.7	16.1	40.1
150	Myanmar	0.609	0.477	21.7	10	21.6	20.5	0.574	26.9	0.389	17.6	0.485	21.9	25.5	16.7	30.7
151	Cambodia	0.606	0.444	26.7	5	26.3	14.9	0.663	28.1	0.348	35.8	0.378	..	..	18.1	..
152	Comoros	0.603	0.356	41.0	–14	39.7	22.2	0.560	44.4	0.317	52.4	0.255	13.6	33.6	14.2	45.3
153	Zimbabwe	0.598	0.406	32.1	1	29.9	22.3	0.511	14.6	0.517	52.9	0.253	15.1	34.8	17.5	50.3
154	Zambia	0.595	0.361	39.3	–8	35.7	23.4	0.546	20.4	0.440	63.4	0.196	11.2	39.1	18.0	51.5
155	Cameroon	0.588	0.361	38.6	–7	37.5	27.9	0.484	31.7	0.354	52.9	0.275	15.0	31.1	13.3	42.2
156	Solomon Islands	0.584	0.483	17.3	22	17.2	11.8	0.686	17.4	0.422	22.5	0.389	18.4	29.2	16.1	37.1
157	Côte d'Ivoire	0.582	0.350	39.9	–10	39.4	28.5	0.461	46.1	0.258	43.4	0.360	19.2	27.8	21.0	35.3
157	Uganda	0.582	0.400	31.3	4	30.6	20.1	0.593	27.9	0.384	43.6	0.282	16.1	34.5	21.4	42.7
159	Rwanda	0.578	0.399	31.0	5	30.2	18.9	0.596	27.4	0.372	44.3	0.285	15.8	35.6	19.9	43.7
160	Papua New Guinea	0.576	0.423	26.6	9	26.5	20.2	0.566	32.1	0.329	27.2	0.405	..	..	16.4	..
161	Togo	0.571	0.363	36.4	0	36.1	26.5	0.483	37.7	0.348	44.1	0.283	17.8	29.6	14.1	37.9
162	Syrian Arab Republic	0.564	..	..	..	..	13.3	0.695	..	..	..	..	23.2	21.1	21.6	26.6
163	Mauritania	0.563	0.374	33.6	4	32.8	19.3	0.602	44.0	0.214	35.0	0.406	20.3	24.6	10.0	32.0
164	Nigeria	0.560	0.379	32.3	6	31.7	38.6	0.325	37.8	0.339	18.6	0.494	18.7	26.7	11.6	35.1
165	Tanzania (United Republic of)	0.555	0.391	29.5	8	29.1	19.9	0.579	26.2	0.325	41.1	0.317	17.4	33.1	18.1	40.5
166	Haiti	0.554	0.337	39.2	–6	38.2	25.3	0.516	37.3	0.302	52.1	0.245	15.8	31.2	17.9	41.1
167	Lesotho	0.550	0.357	35.1	1	33.7	30.0	0.403	19.6	0.453	51.4	0.250	13.5	32.9	14.5	44.9
Low human development																
168	Pakistan	0.544	0.364	33.1	7	32.6	26.0	0.542	43.5	0.205	28.2	0.435	22.7	25.5	16.7	29.6
169	Senegal	0.530	0.340	35.8	–2	34.8	18.0	0.614	47.0	0.186	39.3	0.343	18.8	28.8	13.0	36.2
170	Gambia	0.524	0.329	37.2	–4	36.4	22.2	0.549	47.0	0.215	40.1	0.302	17.5	30.5	15.9	38.8

Continued →

TABLE 3

HDI RANK		Human Development Index (HDI)	Inequality-adjusted HDI (IHDI)			Coefficient of human inequality	Inequality in life expectancy	Inequality-adjusted life expectancy index	Inequality in education[a]	Inequality-adjusted education index	Inequality in income	Inequality-adjusted income index	Income shares held by (%) SDG 10.1			Gini coefficient
		Value	Value	Overall loss (%)	Difference from HDI rank[b]		(%)	Value	(%)	Value	(%)	Value	Poorest 40 percent	Richest 10 percent	Richest 1 percent	
		2023	2023	2023	2023	2023	2023[c]	2023	2023[d]	2023	2022[e]	2022	2010–2023[f]	2010–2023[f]	2023	2010–2023[f]
171	Congo (Democratic Republic of the)	0.522	0.341	34.7	2	34.1	30.8	0.446	26.8	0.402	44.8	0.222	15.1	35.7	19.4	44.7
172	Malawi	0.517	0.365	29.4	12	29.0	19.8	0.584	28.0	0.324	39.3	0.256	18.0	31.0	15.2	38.5
173	Benin	0.515	0.316	38.6	-8	38.5	32.1	0.426	44.0	0.222	39.3	0.334	19.5	27.2	12.8	34.4
174	Guinea-Bissau	0.514	0.331	35.6	1	35.3	28.6	0.484	42.1	0.242	35.3	0.311	19.8	26.1	11.0	33.4
175	Djibouti	0.513	0.341	33.5	6	32.9	24.2	0.536	45.8	0.165	28.7	0.447	15.8	32.3	15.9	41.6
176	Sudan	0.511	0.328	35.8	1	35.3	24.1	0.541	42.5	0.214	39.3	0.306	19.9	27.8	15.4	34.2
177	Liberia	0.510	0.326	36.1	1	35.9	29.2	0.459	42.1	0.287	36.4	0.262	18.8	27.1	12.2	35.3
178	Eritrea	0.503	..	..	..	..	19.4	0.603	..	..	..	..	..	..	13.8	..
179	Guinea	0.500	0.302	39.6	-4	39.0	35.4	0.405	50.1	0.185	31.6	0.367	21.6	23.1	8.7	29.6
180	Ethiopia	0.497	0.326	34.4	3	33.9	22.4	0.565	42.8	0.192	36.5	0.320	19.4	28.5	13.8	35.0
181	Afghanistan	0.496	0.321	35.3	1	34.4	25.2	0.530	48.8	0.196	29.2	0.319	..	..	15.1	..
182	Mozambique	0.493	0.297	39.8	-2	38.7	27.3	0.488	34.3	0.298	54.4	0.180	12.9	41.1	24.8	50.3
183	Madagascar	0.487	0.319	34.5	2	33.9	28.6	0.480	28.3	0.290	44.9	0.234	15.8	33.5	15.2	42.6
184	Yemen	0.470	0.325	30.9	5	29.8	19.7	0.609	46.4	0.209	23.2	0.269	18.8	29.4	25.0	36.7
185	Sierra Leone	0.467	0.281	39.8	-1	39.5	35.1	0.417	47.5	0.194	35.9	0.275	19.6	29.4	15.0	35.7
186	Burkina Faso	0.459	0.273	40.5	-2	40.2	31.1	0.436	46.1	0.172	43.4	0.271	18.5	30.2	14.7	37.4
187	Burundi	0.439	0.286	34.9	2	34.6	24.8	0.505	39.5	0.235	39.5	0.196	18.3	29.9	14.5	37.5
188	Mali	0.419	0.281	32.9	2	32.5	34.0	0.410	40.6	0.148	23.0	0.367	19.1	28.3	12.1	35.7
188	Niger	0.419	0.265	36.8	-1	36.7	37.7	0.395	35.0	0.181	37.4	0.262	21.1	27.8	14.1	32.9
190	Chad	0.416	0.252	39.4	-1	39.5	37.4	0.338	42.9	0.177	38.2	0.267	17.9	29.5	12.8	37.4
191	Central African Republic	0.414	0.253	38.9	1	38.5	35.0	0.374	35.2	0.220	45.5	0.198	15.3	33.1	15.6	43.0
192	Somalia	0.404	0.229	43.3	0	43.1	37.2	0.375	44.6	0.150	47.4	0.214	..	..	16.2	..
193	South Sudan	0.388	0.226	41.8	0	41.7	36.7	0.367	39.6	0.210	48.9	0.149	14.5	33.0	15.4	44.1
Other countries or territories																
..	Korea (Democratic People's Rep. of)	..	..	..	..	..	11.5	0.731	6.7	..	..	..	..	..	14.8	..
..	Monaco	..	..	..	..	..	3.7	0.963	2.2	..	..	..	..	..	11.5	..
Human development groups																
	Very high human development	0.914	0.821	10.2	—	9.9	4.6	0.881	5.0	0.829	20.1	0.757	18.6	27.2	16.5	—
	High human development	0.777	0.640	17.6	—	17.2	8.3	0.786	13.9	0.599	29.3	0.557	17.9	30.3	17.3	—
	Medium human development	0.656	0.457	30.3	—	29.9	18.8	0.616	34.8	0.368	36.1	0.421	19.4	27.1	20.2	—
	Low human development	0.515	0.336	34.8	—	34.4	27.1	0.505	40.4	0.228	35.8	0.330	19.3	29.3	16.3	—
Developing countries		0.712	0.539	24.3	—	24.0	14.6	0.684	24.8	0.459	32.5	0.498	18.6	29.0	18.3	—
Regions																
	Arab States	0.719	0.544	24.3	—	23.9	13.7	0.697	33.6	0.399	24.6	0.577	20.9	26.5	19.3	—
	East Asia and the Pacific	0.775	0.649	16.3	—	15.8	7.8	0.793	11.8	0.600	27.9	0.575	18.8	28.6	16.2	—
	Europe and Central Asia	0.818	0.719	12.1	—	11.9	8.4	0.772	6.6	0.736	20.6	0.653	19.4	27.5	17.3	—
	Latin America and the Caribbean	0.783	0.619	20.9	—	20.1	9.8	0.772	15.3	0.606	35.3	0.508	13.4	36.7	19.6	—
	South Asia	0.672	0.469	30.2	—	29.6	16.5	0.666	36.9	0.356	35.4	0.436	20.5	25.8	21.2	—
	Sub-Saharan Africa	0.568	0.377	33.6	—	33.6	28.0	0.471	33.4	0.328	39.4	0.346	16.7	32.2	16.0	—
Least developed countries		0.560	0.374	33.2	—	32.8	23.9	0.545	35.9	0.289	38.6	0.333	18.1	30.7	16.9	—
Small island developing states		0.739	0.567	23.3	—	22.9	15.1	0.677	21.0	0.503	32.7	0.535	..	..	15.7	—
Organisation for Economic Co-operation and Development		0.916	0.812	11.4	—	11.0	4.8	0.887	6.4	0.815	21.8	0.740	18.0	28.5	16.4	—
World		**0.756**	**0.590**	**22.0**	**—**	**21.6**	**12.9**	**0.715**	**21.5**	**0.514**	**30.4**	**0.559**	**18.7**	**28.6**	**17.9**	**—**

Notes

a	See https://hdr.undp.org/en/composite/IHDI for the list of surveys used to estimate inequalities.
b	Based on countries for which an IHDI value is calculated.
c	Calculated by HDRO from period life tables from UNDESA (2024a).
d	Data refer to 2023 or the most recent year available.
e	Data refer to 2022 or the most recent year available.
f	Data refer to the most recent year available during the period specified.

Definitions

Human Development Index (HDI): A composite index measuring average achievement in three basic dimensions of human development—a long and healthy life, knowledge and a decent standard of living. See *Technical note 1* at https://hdr.undp.org/sites/default/files/2025_HDR/hdr2025_technical_notes.pdf for details on how the HDI is calculated.

Inequality-adjusted HDI (IHDI): HDI value adjusted for inequalities in the three basic dimensions of human development. See *Technical note 2* at https://hdr.undp.org/sites/default/files/2025_HDR/hdr2025_technical_notes.pdf for details on how the IHDI is calculated.

Overall loss: Percentage difference between the IHDI value and the HDI value.

Difference from HDI rank: Difference in ranks on the IHDI and the HDI, calculated only for countries for which an IHDI value is calculated.

Coefficient of human inequality: Average inequality in the three basic dimensions of human development.

Inequality in life expectancy: Inequality in distribution of expected length of life based on data from life tables estimated using the Atkinson inequality index.

Inequality-adjusted life expectancy index: HDI life expectancy index value adjusted for inequality in distribution of expected length of life based on data from life tables listed in *Main data sources*.

Inequality in education: Inequality in distribution of years of schooling based on data from household surveys estimated using the Atkinson inequality index.

Inequality-adjusted education index: HDI education index value adjusted for inequality in distribution of years of schooling based on data from household surveys listed in *Main data sources*.

Inequality in income: Inequality in income distribution based on data from household surveys estimated using the Atkinson inequality index.

Inequality-adjusted income index: HDI income index value adjusted for inequality in income distribution based on data listed in *Main data sources*.

Income shares: Percentage share of income (or consumption) that accrues to the indicated population subgroups.

Income share held by richest 1%: Share of pretax national income held by the richest 1 percent of the population. Pretax national income is the sum of all pretax personal income flows accruing to the owners of the production factors, labour and capital, before the tax/transfer system is taken into account and after the pension system is taken into account.

Gini coefficient: Measure of the deviation of the distribution of income among individuals or households in a country from a perfectly equal distribution. A value of 0 represents absolute equality, a value of 100 absolute inequality.

Main data sources

Column 1: HDRO calculations based on data from Barro and Lee (2018), IMF (2024), UNDESA (2024a), UNESCO Institute for Statistics (2024), United Nations Statistics Division (2025) and World Bank (2024a).

Column 2: Calculated as the geometric mean of the values in the inequality-adjusted life expectancy index, inequality-adjusted education index and inequality-adjusted income index using the methodology in *Technical note 2* (available at https://hdr.undp.org/sites/default/files/2025_HDR/hdr2025_technical_notes.pdf).

Column 3: Calculated based on data in columns 1 and 2.

Column 4: Calculated based on IHDI ranks and recalculated HDI ranks for countries for which an IHDI value is calculated.

Column 5: Calculated as the arithmetic mean of the values in inequality in life expectancy, inequality in education and inequality in income using the methodology in *Technical note 2* (available at https://hdr.undp.org/sites/default/files/2025_HDR/hdr2025_technical_notes.pdf).

Column 6: Calculated based on complete life tables from UNDESA (2024a).

Column 7: Calculated based on inequality in life expectancy and the HDI life expectancy index.

Column 8: Calculated based on data from the Center for Distributive, Labor and Social Studies and the World Bank's Socio-Economic Database for Latin America and the Caribbean, Eurostat's European Union Statistics on Income and Living Conditions, ICF Macro Demographic and Health Surveys, the Luxembourg Income Study database, United Nations Children's Fund Multiple Indicator Cluster Surveys and the United Nations Educational Scientific and Cultural Organization Institute for Statistics using the methodology in *Technical note 2* (available at https://hdr.undp.org/sites/default/files/2025_HDR/hdr2025_technical_notes.pdf).

Column 9: Calculated based on inequality in education and the HDI education index.

Column 10: UNU-WIDER 2023.

Column 11: Calculated based on inequality in income and the HDI income index.

Columns 12, 13 and 15: World Bank 2024a.

Column 14: World Inequality Database 2023.

TABLE 4

Gender Development Index

		Gender Development Index		Human Development Index		SDG 3 Life expectancy at birth (years)		SDG 4.3 Expected years of schooling (years)		SDG 4.4 Mean years of schooling (years)		SDG 8.5 Estimated gross national income per capita[a] (2021 PPP $)	
				Value									
		Value	Group[b]	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male
HDI RANK		2023	2023	2023	2023	2023	2023	2023[c]	2023[c]	2023[c]	2023[c]	2023	2023
Very high human development													
1	Iceland	0.983	1	0.959	0.975	84.5	81.0	20.2 [d]	17.6	14.0 [e]	13.8 [e]	56,441	81,199 [f]
2	Norway	0.995	1	0.967	0.972	84.8	81.7	19.7 [d]	17.9	13.3 [g]	13.0 [g]	94,569 [h]	130,573 [f]
2	Switzerland	0.977	1	0.954	0.976	85.8	82.0	16.8	16.5	13.6 [g]	14.3 [g]	60,385	103,808 [f]
4	Denmark	0.990	1	0.953	0.963	83.9	80.0	19.3 [d]	18.1 [d]	13.2 [g]	12.8 [g]	63,412	88,753 [f]
5	Germany	0.975	1	0.946	0.970	83.8	79.0	17.4	17.3	14.0 [g]	14.6 [g]	52,189	76,218 [f]
5	Sweden	0.988	1	0.950	0.961	85.1	81.4	20.7 [d]	17.4	12.9 [g]	12.6 [g]	55,665	76,391 [f]
7	Australia	0.977	1	0.946	0.968	85.7	82.1	21.5 [d]	19.8 [d]	12.9	12.8	48,588	68,116
8	Hong Kong, China (SAR)	0.976	1	0.941	0.964	88.1 [i]	82.8 [j]	16.9	16.9	12.0	12.8	56,528	85,162 [f]
8	Netherlands	0.971	2	0.938	0.966	83.7	80.5	18.9 [d]	18.2 [d]	12.5 [g]	12.9 [g]	56,539	80,307 [f]
10	Belgium	0.979	1	0.940	0.960	84.3	79.9	20.1 [d]	18.0	12.7 [g]	12.7 [g]	51,965	75,533 [f]
11	Ireland	1.001	1	0.950	0.949	84.5	80.4	19.6 [d]	18.8 [d]	11.9 [g]	11.5 [g]	74,819	107,271 [f]
12	Finland	0.992	1	0.943	0.951	84.7	79.2	20.7 [d]	18.4 [d]	13.2 [g]	12.8 [g]	48,533	65,803
13	Singapore	0.994	1	0.944	0.950	86.2	81.2	16.9	16.6	11.7	12.3	96,100 [h]	125,389 [f]
13	United Kingdom	0.979	1	0.933	0.953	83.2	79.4	18.4 [d]	17.2	13.6	13.4	42,538	66,576
15	United Arab Emirates	0.957	2	0.908	0.949	84.2	82.0	16.1	15.3	12.8	13.1	39,172	89,116 [f]
16	Canada	0.991	1	0.934	0.943	84.8	80.4	16.5	15.3	13.9	13.8	45,016	64,494
17	Liechtenstein	0.964	2	0.919	0.954	85.3	81.8	14.4	16.4	12.2 [k]	12.6 [k]	130,593 [h]	203,518 [f]
17	New Zealand	0.973	2	0.925	0.950	83.8	80.4	19.7 [d]	18.9 [d]	12.9 [g]	12.9 [g]	39,338	55,285
17	United States	1.009	1	0.938	0.929	81.8	76.9	16.8	15.1	14.0	13.8	60,085	87,081 [f]
20	Korea (Republic of)	0.959	2	0.915	0.954	87.2	81.2	16.3	16.9	12.1 [g]	13.3 [g]	38,370	61,120
21	Slovenia	0.997	1	0.927	0.930	84.3	78.9	18.4 [d]	16.7	13.0 [g]	12.9 [g]	37,398	55,248
22	Austria	0.985	1	0.921	0.936	84.3	79.5	16.8	15.8	12.1 [g]	12.6 [g]	51,929	75,395
23	Japan	0.970	2	0.909	0.938	87.7 [i]	81.7	15.5	15.5	12.4 [g]	13.0 [g]	37,017	59,059
24	Malta	0.977	1	0.911	0.932	85.3	81.3	16.6	15.3	12.2 [g]	12.6 [g]	38,808	64,528
25	Luxembourg	0.996	1	0.919	0.922	83.8	80.6	14.5	14.2	12.8 [e]	12.4 [e]	70,537	100,195 [f]
26	France	0.993	1	0.916	0.923	86.1	80.4	16.6	15.6	11.6 [g]	11.9 [g]	46,383	64,286
27	Israel	0.994	1	0.915	0.921	84.6	80.2	15.5	14.4	13.6 [g]	13.5 [g]	41,075	55,089
28	Spain	0.989	1	0.910	0.920	86.3	81.0	18.5 [d]	17.2	10.7 [g]	10.8 [g]	37,689	54,633
29	Czechia	0.987	1	0.908	0.919	82.6	77.0	17.5	16.2	12.8 [g]	13.1 [g]	35,089	56,992
29	Italy	0.975	1	0.901	0.925	85.7	81.6	17.3	16.2	10.7 [g]	11.0 [g]	38,437	67,001
29	San Marino	0.991	1	0.910	0.918	87.1	84.2 [j]	14.8 [g]	14.4 [g]	11.3	11.4	57,818	71,829
32	Andorra	..	..	..	..	86.1	82.1	14.8	14.3	11.5	11.7	..	..
32	Cyprus	0.996	1	0.911	0.915	83.7	79.6	16.9	15.5	12.6 [g]	12.6 [g]	39,336	51,361
34	Greece	0.963	2	0.889	0.923	84.3	79.3	21.0 [d]	20.7 [d]	11.2 [g]	11.9 [g]	27,068	45,015
35	Poland	1.012	1	0.910	0.899	82.4	74.9	17.6	15.8	13.4 [g]	13.0 [g]	33,206	51,802
36	Estonia	1.023	1	0.913	0.893	83.0	74.9	16.9	15.1	13.7 [g]	13.3 [g]	34,599	47,825
37	Saudi Arabia	0.931	3	0.855	0.918	81.2	77.1	17.9	16.4	11.0 [g]	12.0 [g]	20,287	69,767
38	Bahrain	0.957	2	0.870	0.909	82.0	80.7	16.6	15.4	12.1	10.6	24,461	70,143
39	Lithuania	1.022	1	0.903	0.884	80.7	71.2	17.0	15.9	13.7 [g]	13.5 [g]	35,072	49,587
40	Portugal	1.000	1	0.890	0.890	85.1	79.4	17.9	17.1	9.7 [g]	9.7 [g]	36,435	46,152
41	Croatia	0.999	1	0.888	0.889	81.7	75.4	17.3	15.4	11.9 [l]	12.3 [l]	33,291	50,066
41	Latvia	1.026	2	0.899	0.876	80.5	71.6	17.3	15.7	13.7 [g]	13.1 [g]	31,383	45,664
43	Qatar	1.036	2	0.909	0.877	83.4	81.6	15.1	12.3	12.7	10.2	54,169	125,739 [f]
44	Slovakia	0.999	1	0.879	0.880	81.6	75.0	15.5	14.4	13.1 [g]	13.1 [g]	29,901	44,016
45	Chile	0.967	2	0.862	0.891	83.1	79.2	17.2	16.6	11.2 [g]	11.4 [g]	21,087	35,091
46	Hungary	0.989	1	0.864	0.874	80.2	73.7	15.8	15.1	12.2 [g]	12.5 [g]	29,682	45,425
47	Argentina	0.988	1	0.853	0.863	79.9	74.8	20.8 [d]	17.0	11.5 [g]	10.9 [g]	19,464	32,386
48	Montenegro	0.984	1	0.855	0.868	80.3	73.7	16.2	14.9	12.2 [g]	13.3 [g]	22,325	34,173
48	Uruguay	1.017	1	0.863	0.848	81.9	74.2	18.9 [d]	16.1	10.8	10.3	22,306	35,387
50	Oman	0.945	3	0.822	0.870	81.9	78.5	14.1	13.0	12.3	11.7	15,311	48,793
51	Türkiye	0.938	3	0.822	0.876	79.9	74.5	19.7 [d]	19.9 [d]	8.3 [g]	9.7 [g]	21,513	47,535
52	Kuwait	1.011	1	0.849	0.840	81.8	79.3	18.2 [d,g]	13.9 [g]	8.4 [g]	7.1 [g]	29,510	73,825
53	Antigua and Barbuda	1.031	2	0.862	0.836	80.3	74.5	16.8 [g]	14.3 [g]	12.2	11.1	23,694	31,453
54	Seychelles	1.004	1	0.842	0.838	76.5	69.9	20.8 [d]	16.3	11.0 [m]	11.4 [m]	23,994	33,419
55	Bulgaria	1.000	1	0.844	0.844	79.2	72.2	15.7	14.9	11.6 [g]	11.4 [g]	25,852	38,916
55	Romania	0.986	1	0.837	0.849	79.6	72.4	14.6	13.5	11.3	11.8	28,345	51,116
57	Georgia	1.009	1	0.846	0.838	79.1	69.6	17.1	16.5	12.8	12.6	16,596	25,515
58	Saint Kitts and Nevis	..	..	..	..	76.0	68.6	19.7 [d,n]	17.0 [n]	11.1 [o]	10.6 [o]	..	..
59	Panama	1.014	1	0.844	0.833	82.6	76.7	14.0 [g]	12.7 [g]	11.1 [g]	10.5 [g]	29,598	39,169

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						SDG 3		SDG 4.3		SDG 4.4		SDG 8.5	
		Gender Development Index		Human Development Index		Life expectancy at birth		Expected years of schooling		Mean years of schooling		Estimated gross national income per capita[a]	
				Value		(years)		(years)		(years)		(2021 PPP $)	
		Value	Group[b]	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male
HDI RANK		2023	2023	2023	2023	2023	2023	2023[c]	2023[c]	2023[c]	2023[c]	2023	2023
60	Brunei Darussalam	0.993	1	0.829	0.835	77.6	73.3	14.2[p]	13.3[p]	9.3[m]	9.3	56,315	93,032[f]
60	Kazakhstan	1.004	1	0.837	0.833	78.4	70.1	14.2	13.9	12.6[g]	12.5[g]	25,774	36,485
62	Costa Rica	0.975	1	0.818	0.840	83.4	78.1	16.9[g]	15.8[g]	8.9[g]	8.7[g]	15,436	31,586
62	Serbia	0.987	1	0.827	0.838	80.0	73.5	15.7	14.4	11.4[g]	12.0[g]	17,781	29,012
64	Russian Federation	1.023	1	0.840	0.821	79.0	67.3	13.2	13.1	12.5	12.3	31,728	47,866
65	Belarus	1.009	1	0.826	0.820	79.1	69.5	13.8	13.7	12.4[g]	12.3[g]	22,205	31,904
66	Bahamas	1.015	1	0.826	0.814	78.2	70.9	12.2[q]	11.6[q]	12.9[g]	12.8[g]	28,999	33,132
67	Malaysia	0.973	2	0.805	0.828	79.4	74.3	13.1	12.2	11.0	11.2	22,512	41,670
68	North Macedonia	0.955	2	0.794	0.831	79.6	75.1	15.3	14.3	9.6[p]	10.8[p]	15,663	28,957
69	Armenia	1.006	1	0.812	0.807	79.5	71.4	14.9	13.9	11.4[e]	11.3[e]	16,566	24,445
69	Barbados	1.035	2	0.819	0.791	78.6	73.6	18.4[d,g]	14.8[g]	10.4[e]	9.1[e]	14,577	20,313
71	Albania	0.963	2	0.794	0.824	81.4	77.7	14.7	14.3	9.9[e]	10.5[e]	14,123	21,211
72	Trinidad and Tobago	0.990	1	0.801	0.809	76.7	70.4	14.6[r]	13.9[r]	10.9	10.6	20,212	33,937
73	Mauritius	0.971	2	0.790	0.813	78.2	71.9	14.7[g]	13.6[g]	10.0[e]	10.1[e]	16,738	37,829
74	Bosnia and Herzegovina	0.967	2	0.789	0.816	80.9	74.4	13.7	12.6	10.3	11.7	14,574	25,622
	High human development												
75	Iran (Islamic Republic of)	0.875	5	0.724	0.828	79.6	75.8	14.1[g]	13.9[g]	10.9[g]	10.8[g]	4,433	27,375
76	Saint Vincent and the Grenadines	..	..	..	..	74.3	68.7	16.4[q]	16.1[q]	11.4[s]	11.2[s]	..	..
76	Thailand	1.008	1	0.802	0.795	80.9	72.2	15.5[g]	15.2[g]	8.9	9.2	18,717	22,519
78	China	0.976	1	0.786	0.806	80.9	75.2	16.0[g]	15.1[g]	7.8[g]	8.3[g]	16,257	27,580
79	Peru	0.959	2	0.777	0.810	80.1	75.4	15.0[g]	14.8[g]	9.6[g]	10.7[g]	11,653	17,053
80	Grenada	0.984	1	0.783	0.796	78.4	72.4	17.2[g]	16.0[g]	9.3[t]	9.6[t]	11,030	17,645
81	Azerbaijan	0.983	1	0.781	0.795	77.1	71.6	12.9	12.9	11.0	11.2	17,656	23,803
81	Mexico	0.976	1	0.777	0.797	77.8	72.2	15.0	13.9	9.2[g]	9.5[g]	15,410	28,611
83	Colombia	0.992	1	0.784	0.790	80.5	75.0	14.5	14.0	9.2[g]	8.9[g]	15,384	22,035
84	Brazil	1.002	1	0.785	0.783	79.0	72.8	16.5	15.1	8.6[g]	8.2[g]	13,886	22,268
84	Palau	0.992	1	0.781	0.788	71.8	67.2	15.1	13.1	13.3[m]	13.3[m]	12,385	19,156
86	Moldova (Republic of)	1.029	2	0.795	0.773	75.5	66.6	15.0[g]	14.3[g]	11.9	11.7	15,025	16,853
87	Ukraine	1.038	2	0.792	0.763	80.2	66.9	13.5	13.1	11.4[e]	10.7[e]	13,295	21,120
88	Ecuador	0.998	1	0.776	0.777	80.1	74.7	15.4	14.4	8.9	9.0	12,333	15,649
89	Dominican Republic	1.024	1	0.783	0.765	77.0	70.5	14.6	12.6	9.9[g]	9.0[g]	17,368	26,730
89	Guyana	0.992	1	0.771	0.777	73.9	66.5	13.3[r]	12.7[r]	8.8[e]	8.6[e]	32,865	61,804
89	Sri Lanka	0.951	2	0.750	0.789	80.6	74.2	13.6	12.6	10.7	10.8	6,970	18,637
92	Tonga	0.998	1	0.763	0.764	76.4	69.4	19.0[d,g]	16.6[g]	11.0[e]	10.8[e]	5,957	9,081
93	Maldives	0.986	1	0.755	0.766	82.8	79.7	14.1	11.6	7.4[e]	7.4[e]	12,134	23,702
93	Viet Nam	0.997	1	0.765	0.767	79.3	69.9	15.5[u]	15.4	8.5	9.5	11,422	14,711
95	Turkmenistan	..	..	..	..	72.8	66.9	13.2	13.2	10.9[g]	11.5[g]	..	..
96	Algeria	0.887	5	0.702	0.791	77.7	74.9	16.2	14.8	6.9[g]	7.9[g]	5,284	24,554
97	Cuba	0.975	1	0.750	0.769	80.5	75.7	14.6	13.2	10.7[e]	10.5[e]	5,994	10,900
98	Dominica	..	..	..	..	74.5	68.2	15.0[g]	13.3[g]	10.0	10.2	..	..
99	Paraguay	0.988	1	0.750	0.759	77.0	70.9	14.4[g]	13.6[g]	8.9[g]	8.9[g]	11,930	18,555
100	Egypt	0.895	5	0.695	0.777	73.8	69.5	13.0[g]	13.2[g]	10.7[g]	9.7[g]	5,077	27,143
100	Jordan	0.861	5	0.677	0.787	80.2	75.7	13.6	12.7	9.7	10.9	2,745	15,296
102	Lebanon	0.992	1	0.749	0.755	79.7	75.7	12.1[u]	11.4[u]	13.1[v]	9.1[v]	6,068	16,829
103	Saint Lucia	1.016	1	0.754	0.742	76.3	69.3	13.4	12.1	8.9[g]	8.4[g]	16,790	25,106
104	Mongolia	1.030	2	0.757	0.735	76.4	67.2	14.4	13.1	9.9[p]	8.9[p]	11,204	18,386
105	Tunisia	0.931	3	0.712	0.765	79.1	73.9	15.6[g]	13.8[g]	7.0	8.2	6,063	18,092
106	South Africa	0.996	1	0.738	0.741	69.6	62.6	14.4	13.2	11.5	11.7	10,794	16,755
107	Uzbekistan	0.951	2	0.718	0.755	75.4	69.5	12.5	12.4	11.8	12.1	5,840	11,759
108	Bolivia (Plurinational State of)	0.961	2	0.718	0.748	71.1	66.1	15.7[g]	15.5[g]	9.4[g]	10.7[g]	8,010	10,874
108	Gabon	0.994	1	0.728	0.733	71.1	65.9	12.6[q]	12.3[q]	10.5	8.9	13,264	24,269
108	Marshall Islands	0.960	2	0.716	0.746	69.3	64.9	17.0	15.8	11.5[m]	11.8[m]	5,186	9,161
111	Botswana	0.997	1	0.730	0.732	71.7	66.7	11.8	11.1	10.4	10.5	15,531	18,444
111	Fiji	0.948	3	0.706	0.745	69.4	65.3	14.4	13.3	10.4	10.3	7,531	18,235
113	Indonesia	0.945	3	0.704	0.745	73.3	69.0	13.6	13.1	8.4[g]	9.0[g]	9,073	18,284
114	Suriname	0.993	1	0.717	0.722	76.8	70.5	11.3	10.6	8.6[g]	8.2[g]	12,734	21,958
115	Belize	0.981	1	0.713	0.727	76.5	70.9	12.3	11.6	8.8	8.8	9,453	15,179
115	Libya	0.955	2	0.700	0.733	70.4	68.3	13.0[t]	12.8[t]	8.4[o]	7.2[o]	12,125	27,282
117	Jamaica	1.013	1	0.723	0.713	74.0	69.0	13.5[g]	11.3[g]	10.2	9.6	8,153	12,002
117	Kyrgyzstan	0.959	2	0.701	0.731	75.2	68.2	12.8	12.6	12.0[g]	12.2[g]	4,120	8,080

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	Gender Development Index		Human Development Index		SDG 3 Life expectancy at birth (years)		SDG 4.3 Expected years of schooling (years)		SDG 4.4 Mean years of schooling (years)		SDG 8.5 Estimated gross national income per capita[a] (2021 PPP $)	
	Value	Group[b]	Value: Female	Value: Male	Female	Male	Female	Male	Female	Male	Female	Male
HDI RANK	2023	2023	2023	2023	2023	2023	2023[c]	2023[c]	2023[c]	2023[c]	2023	2023
117 Philippines	0.984	1	0.709	0.721	72.8	66.9	13.1	12.1	10.2	9.8	7,744	13,732
120 Morocco	0.859	5	0.642	0.748	77.6	73.2	15.1	15.1	5.3	7.1	3,221	13,990
121 Venezuela (Bolivarian Republic of)	0.993	1	0.699	0.704	76.5	68.7	13.0 [s]	11.6 [s]	10.0 [m]	9.7 [s]	5,040	9,323
122 Samoa	0.955	2	0.687	0.719	73.7	69.9	13.0	11.9	11.8 [g]	10.9 [g]	3,724	8,150
123 Nicaragua	0.952	2	0.685	0.719	77.4	72.3	11.7	11.3	9.9	10.0	4,676	9,161
124 Nauru	0.955	2	0.689	0.722	64.0	60.3	13.1 [t]	12.6 [u]	9.3 [t]	10.2 [t]	15,192	23,930
Medium human development												
125 Bhutan	0.958	2	0.681	0.711	75.0	71.3	13.7 [g]	12.6 [g]	5.2 [o]	6.3 [o]	10,750	16,531
126 Eswatini (Kingdom of)	0.964	2	0.682	0.708	67.0	61.2	14.7 [g]	15.8 [g]	8.5	8.9	8,446	11,447
126 Iraq	0.793	5	0.592	0.747	74.1	70.4	11.8 [w]	12.9 [w]	5.6 [r]	8.0 [r]	2,909	22,332
128 Tajikistan	0.926	3	0.662	0.715	74.0	69.6	10.5 [g]	11.2 [g]	10.9 [e]	11.6 [e]	4,051	7,504
129 Tuvalu	0.969	2	0.675	0.697	70.7	63.8	12.6 [t]	12.1 [t]	10.6 [g]	10.9 [g]	4,963	8,957
130 Bangladesh	0.918	4	0.650	0.708	76.4	73.0	12.4	11.9	6.2	7.3	5,280	11,820
130 India	0.874	5	0.631	0.722	73.6	70.5	13.0	12.9	5.8	8.0	4,543	13,273
132 El Salvador	0.983	1	0.670	0.682	76.3	67.5	11.5	10.7	7.0	7.6	7,699	13,795
133 Equatorial Guinea	..	..	..	..	65.7	62.0	12.1 [u]	12.9 [t]	..	..	..	..
133 Palestine, State of	0.945	3	0.638	0.676	71.5	59.7	13.8	12.2	10.2	10.0	2,339	10,806
135 Cabo Verde	0.964	2	0.653	0.677	79.2	72.9	11.6 [g]	11.1 [g]	5.8 [o]	6.3 [o]	5,998	10,259
136 Namibia	1.011	1	0.668	0.661	71.3	63.3	11.8 [x]	11.8 [x]	7.5 [e]	7.0 [e]	9,353	12,555
137 Guatemala	0.934	3	0.638	0.683	74.9	70.3	10.8	10.5	5.3	6.5	8,528	16,454
138 Congo	0.924	4	0.622	0.673	67.5	64.1	13.4 [g]	12.1 [g]	7.3 [e]	9.4 [e]	4,214	7,591
139 Honduras	0.964	2	0.633	0.657	75.5	70.3	10.6 [g]	9.7 [g]	7.0 [g]	8.1 [g]	4,914	7,199
140 Kiribati	0.976	1	0.634	0.650	68.2	64.6	12.4 [y]	11.3 [y]	9.3 [o]	9.0 [o]	3,949	6,009
141 Sao Tome and Principe	0.980	1	0.633	0.646	73.7	66.2	13.2 [r]	12.7 [r]	5.4 [g]	6.8 [g]	4,982	6,192
142 Timor-Leste	0.939	3	0.613	0.653	69.4	66.1	13.5 [x]	13.0 [x]	5.8 [x]	6.8 [x]	4,188	6,661
143 Ghana	0.933	3	0.607	0.651	67.9	63.1	11.3	11.5	6.1	8.3	5,958	7,736
143 Kenya	0.944	3	0.610	0.646	65.9	61.5	11.5 [x]	11.5 [x]	8.0	9.3	4,641	6,586
145 Nepal	0.858	5	0.567	0.661	71.8	68.8	12.4	14.0	3.5	5.8	3,185	6,390
146 Vanuatu	0.952	2	0.604	0.635	73.9	69.4	11.9 [g]	11.7 [g]	6.6 [o]	7.5 [o]	2,857	3,940
147 Lao People's Democratic Republic	0.911	4	0.583	0.640	71.3	66.8	8.8	9.7	5.1 [e]	7.0 [e]	6,691	9,507
148 Angola	0.906	4	0.584	0.645	67.1	62.1	11.5	12.9	4.5 [x]	7.3 [x]	5,854	7,425
149 Micronesia (Federated States of)	0.953	2	0.598	0.628	71.1	63.5	11.5 [t]	11.6 [u]	6.9 [o]	7.8 [o]	3,157	5,348
150 Myanmar	0.947	3	0.589	0.622	70.2	63.8	12.0 [v]	11.1 [v]	6.1 [z]	6.7 [z]	3,122	6,731
151 Cambodia	0.939	3	0.586	0.625	73.2	68.0	11.4	10.9	4.4	6.2	4,067	5,832
152 Comoros	0.929	3	0.581	0.625	68.9	64.8	13.7 [g]	12.9 [g]	5.2	6.9	2,657	4,295
153 Zimbabwe	0.944	3	0.581	0.616	65.0	60.2	10.7 [g]	11.4 [g]	8.3 [g]	9.7 [g]	3,145	3,915
154 Zambia	0.949	3	0.580	0.611	68.7	63.9	11.2 [aa]	10.9 [aa]	6.6 [e]	8.4 [e]	3,132	3,768
155 Cameroon	0.898	5	0.556	0.619	65.9	61.5	10.2	11.4	5.7 [e]	7.6 [e]	3,629	5,870
156 Solomon Islands	0.927	3	0.565	0.610	72.0	69.2	11.0 [t]	11.6 [u]	5.5 [o]	6.8 [o]	2,469	3,072
157 Côte d'Ivoire	0.910	4	0.553	0.607	64.1	60.0	11.1	11.7	4.0	5.6	5,161	8,253
157 Uganda	0.908	4	0.556	0.612	71.1	65.3	11.2 [x]	12.0 [x]	5.2 [g]	7.9 [g]	2,280	3,201
159 Rwanda	0.922	4	0.552	0.599	69.9	65.5	12.5	12.6	4.5	5.3	2,159	3,824
160 Papua New Guinea	0.926	3	0.554	0.599	69.1	63.7	10.9 [x]	12.1 [x]	4.3 [e]	5.7 [e]	3,436	4,475
161 Togo	0.865	5	0.535	0.618	62.9	62.5	12.9 [g]	14.5 [g]	4.5 [g]	7.4 [g]	2,470	3,237
162 Syrian Arab Republic	0.787	5	0.477	0.607	74.4	69.8	7.2 [q]	7.7 [q]	5.1 [m]	6.7 [m]	1,149	6,688
163 Mauritania	0.886	5	0.528	0.595	70.5	66.5	8.1 [g]	7.8 [g]	4.2 [e]	5.9 [e]	3,604	9,038
164 Nigeria	0.892	5	0.528	0.592	54.7	54.2	10.2	10.8	6.6	8.7	5,001	6,126
165 Tanzania (United Republic of)	0.951	2	0.542	0.569	69.8	64.2	8.7	8.5	5.5	6.7	2,977	4,062
166 Haiti	0.932	3	0.534	0.573	68.3	61.7	10.8 [t]	11.0 [t]	4.8 [ab]	6.1 [ab]	2,256	3,627
167 Lesotho	1.006	1	0.550	0.547	60.0	54.6	11.3 [g]	10.7 [g]	8.4 [g]	7.0 [g]	2,495	3,592
Low human development												
168 Pakistan	0.838	5	0.485	0.579	70.2	65.3	7.3	8.6	4.0 [g]	4.6 [g]	2,173	8,724
169 Senegal	0.924	4	0.509	0.550	70.8	66.8	9.9	8.4	2.5 [g]	3.8 [g]	2,665	5,686
170 Gambia	0.959	2	0.515	0.537	67.5	64.2	9.9 [x]	8.1 [x]	3.9 [x]	5.8 [x]	2,561	3,065
171 Congo (Democratic Republic of the)	0.886	5	0.491	0.554	64.0	59.8	10.4 [g]	11.5 [g]	6.1 [e]	9.0 [e]	1,215	1,650
172 Malawi	0.925	3	0.497	0.537	70.6	64.1	10.0	9.8	4.3 [p]	6.4 [p]	1,356	1,925
173 Benin	0.866	5	0.479	0.553	62.2	59.3	9.8	11.1	2.0	4.6	3,329	4,279
174 Guinea-Bissau	0.878	5	0.485	0.553	66.4	61.7	10.5 [w]	11.7 [w]	2.5	5.1	1,996	2,820
175 Djibouti	0.814	5	0.453	0.556	68.5	63.5	5.8 [g]	6.6 [g]	2.7 [s]	5.1 [s]	3,101	9,690
176 Sudan	0.813	5	0.441	0.542	69.6	63.3	8.4 [g]	8.8 [g]	3.6	4.3	909	4,742

Continued →

TABLE 4

		Gender Development Index		Human Development Index		SDG 3 Life expectancy at birth		SDG 4.3 Expected years of schooling		SDG 4.4 Mean years of schooling		SDG 8.5 Estimated gross national income per capita[a]	
				Value		(years)		(years)		(years)		(2021 PPP $)	
		Value	Group[b]	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male
HDI RANK		2023	2023	2023	2023	2023	2023	2023[c]	2023[c]	2023[c]	2023[c]	2023	2023
177	Liberia	0.865	5	0.473	0.547	63.4	60.9	10.1	10.8	4.7 [g]	7.8 [g]	1,279	1,798
178	Eritrea	..	..	..	..	70.7	66.5	6.9 [g]	7.8 [g]	4.0 [o]	5.7 [o]	..	..
179	Guinea	0.828	5	0.451	0.545	61.9	59.5	9.4 [g]	11.4 [g]	1.5 [g]	3.6 [g]	2,550	4,460
180	Ethiopia	0.886	5	0.465	0.525	70.7	64.1	8.6 [x]	9.7 [x]	1.7 [g]	3.2 [g]	2,056	3,531
181	Afghanistan	0.660	5	0.379	0.575	67.5	64.5	8.1 [g]	13.4 [g]	1.2	3.9	721	3,198
182	Mozambique	0.920	4	0.473	0.514	66.5	60.3	10.5 [g]	11.2 [g]	3.7	5.7	1,198	1,523
183	Madagascar	0.934	3	0.469	0.502	65.4	61.9	9.2 [g]	8.9 [g]	4.3	4.9	1,345	1,965
184	Yemen	0.407	5	0.221	0.543	71.4	67.2	6.5 [s]	8.1 [s]	3.6	7.5	137	1,877
185	Sierra Leone	0.830	5	0.423	0.510	63.5	60.1	7.8 [u]	10.3 [u]	2.5 [g]	4.8 [g]	1,437	1,992
186	Burkina Faso	0.881	5	0.428	0.486	63.2	58.9	8.8	8.7	1.6	3.1	1,634	3,153
187	Burundi	0.932	3	0.424	0.456	65.7	61.6	10.1 [g]	9.6 [g]	2.8 [g]	4.3 [g]	764	955
188	Mali	0.812	5	0.372	0.459	61.9	59.0	6.3 [g]	7.7 [g]	1.1 [p]	2.2 [p]	1,409	3,257
188	Niger	0.855	5	0.385	0.451	62.1	60.3	7.5 [g]	9.1 [g]	1.0 [e]	1.8 [e]	1,276	1,895
190	Chad	0.787	5	0.365	0.464	57.0	53.2	7.0 [g]	9.6 [g]	1.3 [g]	3.5 [g]	1,248	2,245
191	Central African Republic	..	..	..	..	59.3	55.3	6.2 [g]	8.6 [g]	2.7 [e]	5.4 [e]	..	..
192	Somalia	0.793	5	0.354	0.447	61.4	56.4	7.5 [t]	8.1 [t]	0.9	2.9	790	2,156
193	South Sudan	..	..	..	..	60.6	54.6	4.5 [g]	6.7 [g]	4.8 [ac]	6.2 [ac]	..	..
Other countries or territories													
	Korea (Democratic People's Rep. of)	..	..	..	..	75.7	71.5	11.9 [g]	12.5 [g]	..	..	..	..
	Monaco	..	..	..	..	88.5 [i]	84.4 [j]	22.3 [d]	21.1 [d]	..	..	..	..
Human development groups													
	Very high human development	0.989	—	0.908	0.918	82.9	77.2	16.9	15.9	12.4	12.6	41,543	64,643
	High human development	0.971	—	0.764	0.786	78.6	72.9	15.0	14.2	8.6	8.8	13,044	23,717
	Medium human development	0.883	—	0.610	0.691	71.0	67.7	12.0	12.2	5.9	7.8	4,456	11,072
	Low human development	0.836	—	0.463	0.554	67.4	62.7	8.4	9.5	3.3	4.8	1,618	4,475
Developing countries		0.934	—	0.685	0.733	74.4	69.8	12.6	12.6	7.3	8.3	8,845	17,725
Regions													
	Arab States	0.871	—	0.655	0.752	74.5	70.6	11.9	12.0	7.5	8.6	5,493	25,449
	East Asia and the Pacific	0.973	—	0.763	0.785	78.9	73.1	14.9	14.2	8.0	8.5	14,435	24,478
	Europe and Central Asia	0.970	—	0.803	0.829	78.4	71.2	15.6	15.5	10.5	10.9	16,367	30,624
	Latin America and the Caribbean	0.989	—	0.777	0.785	78.5	72.7	15.3	14.1	9.2	9.1	13,703	22,526
	South Asia	0.872	—	0.618	0.709	73.6	70.2	12.0	12.3	5.9	7.7	4,246	12,996
	Sub-Saharan Africa	0.916	—	0.544	0.594	64.6	60.4	10.1	10.7	5.4	7.1	3,623	5,173
Least developed countries		0.889	—	0.525	0.591	68.9	64.2	9.8	10.5	4.3	5.9	2,549	4,832
Small island developing states		0.979	—	0.731	0.747	74.7	69.2	12.8	12.4	8.5	8.8	15,508	23,151
Organisation for Economic Co-operation and Development		0.986	—	0.908	0.921	83.1	78.0	17.0	16.0	12.2	12.5	41,745	63,915
World		**0.955**	**—**	**0.737**	**0.772**	**75.9**	**71.0**	**13.1**	**13.0**	**8.4**	**9.2**	**14,943**	**25,751**

Notes

a	Because disaggregated income data are not available, data are crudely estimated. See *Definitions* and *Technical note 3 at* https://hdr.undp.org/sites/default/files/2025_HDR/hdr2025_technical_notes.pdf for details on how the Gender Development Index is calculated.
b	Countries are divided into five groups by absolute deviation from gender parity in HDI values.
c	Data refer to 2023 or the most recent year available.
d	In calculating the HDI value, expected years of schooling is capped at 18 years.
e	Updated by HDRO based on data from Barro and Lee (2018) and UNESCO Institute for Statistics (2024).
f	In calculating the male HDI value, estimated gross national income per capita is capped at $75,000.
g	Updated by HDRO based on data from UNESCO Institute for Statistics (2024).
h	In calculating the female HDI value, estimated gross national income per capita is capped at $75,000.
i	In calculating the female HDI value, life expectancy at birth is capped at 87.5 years.
j	In calculating the male HDI value, life expectancy at birth is capped at 82.5 years.
k	Updated by HDRO using the mean years of schooling trend of Austria and data from UNESCO Institute for Statistics (2024).
l	Updated by HDRO based on data from Eurostat (2024) and UNESCO Institute for Statistics (2024).
m	HDRO estimate based on data from Robert Barro and Jong-Wha Lee, Eurostat's EU Statistics on Income and Living Conditions, ICF Macro Demographic and Health Surveys, the United Nations Educational, Scientific and Cultural Organization (UNESCO) Institute for Statistics and United Nations Children's Fund (UNICEF) Multiple Indicator Cluster Surveys.
n	Refers to 2015 based on UNESCO Institute for Statistics (2024).
o	HDRO estimate based on data from Robert Barro and Jong-Wha Lee, ICF Macro Demographic and Health Surveys, the Organisation for Economic Co-operation and Development, the UNESCO Institute for Statistics and UNICEF Multiple Indicator Cluster Surveys.
p	Refers to 2020 based on UNESCO Institute for Statistics (2024).
q	HDRO estimate based on data from the Center for Distributive, Labor and Social Studies and the World Bank's Socio-Economic Database for Latin America and the Caribbean, ICF Macro Demographic and Health Surveys, the UNESCO Institute for Statistics and UNICEF Multiple Indicator Cluster Surveys.
r	Updated by HDRO based on data from UNESCO Institute for Statistics (2024) and UNICEF Multiple Indicator Cluster Surveys for various years.
s	Updated by HDRO based on data from UNESCO Institute for Statistics (2024) and estimates using cross-country regression.
t	Based on HDRO estimates using cross-country regression.
u	HDRO estimate based on data from ICF Macro Demographic and Health Surveys, the UNESCO Institute for Statistics and UNICEF Multiple Indicator Cluster Surveys.
v	Refers to 2018 based on UNESCO Institute for Statistics (2024).
w	Updated by HDRO based on data from UNICEF Multiple Indicator Cluster Surveys for various years.
x	Updated by HDRO based on data from ICF Macro Demographic and Health Surveys for various years and UNESCO Institute for Statistics (2024).
y	Updated by HDRO based on data from UNICEF Multiple Indicator Cluster Surveys for various years and estimates using cross-country regression.
z	Refers to 2019 based on UNESCO Institute for Statistics (2024).
aa	Updated by HDRO based on data from ICF Macro Demographic and Health Surveys for various years.
ab	Refers to 2017 based on UNESCO Institute for Statistics (2024).
ac	Refers to 2008 based on UNESCO Institute for Statistics (2024).

Definitions

Gender Development Index: Ratio of female to male HDI values. See *Technical note 3* at https://hdr.undp.org/sites/default/files/2025_HDR/hdr2025_technical_notes.pdf for details on how the Gender Development Index is calculated.

Gender Development Index groups: Countries are divided into five groups by absolute deviation from gender parity in HDI values. Group 1 comprises countries with high equality in HDI achievements between women and men (absolute deviation of less than 2.5 percent), group 2 comprises countries with medium to high equality in HDI achievements between women and men (absolute deviation of 2.5–5 percent), group 3 comprises countries with medium equality in HDI achievements between women and men (absolute deviation of 5–7.5 percent), group 4 comprises countries with medium to low equality in HDI achievements between women and men (absolute deviation of 7.5–10 percent) and group 5 comprises countries with low equality in HDI achievements between women and men (absolute deviation from gender parity of more than 10 percent).

Human Development Index (HDI): A composite index measuring average achievement in three basic dimensions of human development—a long and healthy life, knowledge and a decent standard of living. See *Technical note 1* at https://hdr.undp.org/sites/default/files/2025_HDR/hdr2025_technical_notes.pdf for details on how the HDI is calculated.

Life expectancy at birth: Number of years a newborn infant could expect to live if prevailing patterns of age-specific mortality rates at the time of birth stay the same throughout the infant's life.

Expected years of schooling: Number of years of schooling that a child of school entrance age can expect to receive if prevailing patterns of age-specific enrolment rates persist throughout the child's life.

Mean years of schooling: Average number of years of education received by people ages 25 and older, converted from educational attainment levels using official durations of each level.

Estimated gross national income per capita: Derived from the ratio of female to male wages, female and male shares of economically active population and gross national income (in 2021 purchasing power parity terms). See *Technical note 3* at https://hdr.undp.org/sites/default/files/2025_HDR/hdr2025_technical_notes.pdf for details.

Main data sources

Column 1: Calculated based on data in columns 3 and 4.

Column 2: Calculated based on data in column 1.

Columns 3 and 4: HDRO calculations based on data from Barro and Lee (2018), IMF (2024), UNDESA (2024a), UNESCO Institute for Statistics (2024), United Nations Statistics Division (2025) and World Bank (2024a).

Columns 5 and 6: UNDESA 2024a.

Columns 7 and 8: ICF Macro Demographic and Health Surveys, UNESCO Institute for Statistics 2024 and UNICEF Multiple Indicator Cluster Surveys.

Columns 9 and 10: Barro and Lee 2018, Eurostat 2024, ICF Macro Demographic and Health Surveys, UNESCO Institute for Statistics 2024 and UNICEF Multiple Indicator Cluster Surveys.

Columns 11 and 12: HDRO calculations based on ILO (2024), IMF (2024), UNDESA (2024a), United Nations Statistics Division (2025) and World Bank (2024a).

Gender Inequality Index

		Gender Inequality Index		SDG 3.1 Maternal mortality ratio (deaths per 100,000 live births)	SDG 3.7 Adolescent birth rate (births per 1,000 women ages 15–19)	SDG 5.5 Share of seats in parliament (% held by women)	SDG 4.4 Population with at least some secondary education (% ages 25 and older)		Labour force participation rate[a] (% ages 15 and older)	
		Value	Rank				Female	Male	Female	Male
HDI RANK		2023	2023	2020	2023	2023	2023[b]	2023[b]	2023	2023
Very high human development										
1	Iceland	0.024	7	3	3.4	47.6	99.9	99.6	70.5	79.3
2	Norway	0.004	2	2	1.4	46.2	95.9	98.5	62.1	69.2
2	Switzerland	0.010	4	7	1.5	37.8	98.0	98.3	62.6	72.9
4	Denmark	0.003	1	5	1.1	43.6	91.0	92.5	59.7	67.7
5	Germany	0.057	21	4	5.5	35.3	93.6	94.3	56.4	66.7
5	Sweden	0.007	3	5	1.8	46.4	94.9	94.1	64.4	70.6
7	Australia	0.056	20	3	6.7	44.5	92.3	93.5	62.8	71.7
8	Hong Kong, China (SAR)	..	..	..	1.1	..	77.9	84.1	52.2	63.6
8	Netherlands	0.013	5	4	1.9	39.1	91.1	92.7	64.1	73.1
10	Belgium	0.031	8	5	3.7	43.5	88.3	91.0	50.7	59.5
11	Ireland	0.054	19	5	4.1	27.4	90.4	89.9	60.4	70.8
12	Finland	0.021	6	8	3.1	46.0	91.6	91.6	58.5	63.8
13	Singapore	0.031	8	7	2.2	29.1	82.9	87.8	62.6	74.9
13	United Kingdom	0.083	31	10	8.4	31.5	99.1	99.0	58.1	66.6
15	United Arab Emirates	0.040	13	9	3.1	50.0	83.4	87.0	54.5	90.8
16	Canada	0.052	18	11	4.8	35.8	96.1	96.5	61.6	69.7
17	Liechtenstein	..	..	..	1.7	28.0	..	..	52.8	67.2
17	New Zealand	0.082	30	7	10.9	44.3	82.9[c]	82.3[c]	67.6	76.7
17	United States	0.169	45	21	13.1	28.2	97.9	97.8	57.3	68.1
20	Korea (Republic of)	0.038	12	8	0.5	19.1	85.0	94.2	56.1	73.4
21	Slovenia	0.042	14	5	3.5	31.5	98.3	98.9	53.8	63.2
22	Austria	0.033	10	5	3.8	42.8	98.8	98.7	56.8	66.6
23	Japan	0.059	22	4	1.7	15.7	98.2[d]	99.1[d]	54.8	71.4
24	Malta	0.111	36	3	10.4	27.8	85.0	90.4	57.2	73.2
25	Luxembourg	0.044	17	6	4.0	33.3	90.1	91.3	58.2	66.2
26	France	0.034	11	8	3.5	37.2	90.5	92.8	52.8	60.1
27	Israel	0.080	27	3	6.2	24.2	90.7	92.7	61.4	68.9
28	Spain	0.043	15	3	4.8	43.7	81.5	85.0	53.4	63.0
29	Czechia	0.088	32	3	6.0	23.8	99.0	99.4	51.8	68.5
29	Italy	0.043	15	5	2.9	33.6	79.8	86.2	41.5	58.8
29	San Marino	..	..	..	1.2	33.3	87.2	88.3	70.4	70.6
32	Andorra	..	..	..	3.5	50.0	81.7	84.6	..	..
32	Cyprus	0.252	64	68	7.0	14.3	84.1	87.8	60.9	70.3
34	Greece	0.103	34	8	7.0	23.0	73.8	80.4	44.8	60.0
35	Poland	0.081	29	2	6.2	27.5	87.5[c]	91.4[c]	52.0	66.3
36	Estonia	0.061	23	5	5.0	28.7	98.7	98.7	62.0	71.6
37	Saudi Arabia	0.228	61	16	11.1	19.9	75.7	81.5	34.6	83.6
38	Bahrain	0.165	44	16	7.5	22.5	88.6	79.9	41.5	85.1
39	Lithuania	0.070	24	9	5.9	28.4	96.9	98.1	58.5	68.5
40	Portugal	0.076	26	12	7.0	36.1	64.1	65.4	55.6	63.9
41	Croatia	0.074	25	5	6.6	31.8	93.5	97.5	47.3	57.6
41	Latvia	0.117	38	18	7.6	32.0	97.2	98.8	55.7	67.9
43	Qatar	0.195	52	8	5.7	4.4	86.7	70.2	61.7	95.3
44	Slovakia	0.176	48	5	24.6	22.0	99.1	99.2	56.3	67.3
45	Chile	0.102	33	15	6.5	32.7	86.0	88.5	52.0	71.4
46	Hungary	0.213	54	15	17.5	14.1	98.3	99.1	54.5	68.4
47	Argentina	0.264	70	45	26.4	43.8	74.3[e]	72.2[e]	53.2	72.2
48	Montenegro	0.121	40	6	9.4	21.0	90.1	96.2	52.2	66.1
48	Uruguay	0.218	56	19	26.2	26.9	63.2	59.3	56.5	73.4
50	Oman	0.222	57	17	6.0	10.2	93.3	98.7	39.9	86.5
51	Türkiye	0.227	59	17	12.1	19.8	62.0[c]	80.4[c]	35.8	71.2
52	Kuwait	0.188	51	7	1.6	3.1	62.7[c]	57.8[c]	47.3	85.9
53	Antigua and Barbuda	0.240	63	21	32.9	22.9	88.0	76.6	69.6	76.0
54	Seychelles	..	..	3	54.5	22.9	..	..	61.3	65.5
55	Bulgaria	0.208	53	7	39.1	24.2	95.7	97.1	49.8	62.2
55	Romania	0.227	59	10	33.8	18.9	91.0	95.0	41.9	61.9
57	Georgia	0.257	66	28	21.1	18.4	98.2	98.7	53.7	69.6
58	Saint Kitts and Nevis	..	..	..	35.2	31.3	..	..	..	..
59	Panama	0.374	94	50	57.3	22.9	67.7	65.3	50.4	74.3

Continued →

HDI RANK		Gender Inequality Index Value	Gender Inequality Index Rank	SDG 3.1 Maternal mortality ratio (deaths per 100,000 live births)	SDG 3.7 Adolescent birth rate (births per 1,000 women ages 15–19)	SDG 5.5 Share of seats in parliament (% held by women)	SDG 4.4 Population with at least some secondary education (% ages 25 and older) Female	SDG 4.4 Population with at least some secondary education (% ages 25 and older) Male	Labour force participation rate[a] (% ages 15 and older) Female	Labour force participation rate[a] (% ages 15 and older) Male
		2023	2023	2020	2023	2023	2023[b]	2023[b]	2023	2023
60	Brunei Darussalam	0.257	66	44	8.5	11.8	86.0	88.8	54.4	72.3
60	Kazakhstan	0.182	50	13	18.2	19.6	100.0 [c]	100.0 [c]	63.3	74.6
62	Costa Rica	0.217	55	22	26.3	47.4	52.1	52.9	43.9	69.7
62	Serbia	0.117	38	10	13.7	34.8	91.2 [c]	96.8 [c]	51.5	65.5
64	Russian Federation	0.169	45	14	13.0	17.8	99.3	99.1	56.2	70.5
65	Belarus	0.080	27	1	8.6	34.7	99.3 [c]	99.9 [c]	65.3	74.9
66	Bahamas	0.325	81	77	24.6	20.0	96.2	97.7	98.7	96.8
67	Malaysia	0.172	47	21	6.0	14.7	79.0	82.1	55.8	81.9
68	North Macedonia	0.112	37	3	13.0	42.5	68.3	76.2	42.5	61.5
69	Armenia	0.180	49	27	13.4	35.5	99.1	99.3	61.6	76.8
69	Barbados	0.297	76	39	45.3	32.7	95.9 [e]	86.4 [e]	54.9	62.7
71	Albania	0.107	35	8	12.8	35.7	90.5	93.9	57.8	70.9
72	Trinidad and Tobago	0.262	69	27	36.0	33.8	73.0	70.7	46.7	64.2
73	Mauritius	0.352	87	84	19.8	20.0	60.4	71.3	46.9	69.7
74	Bosnia and Herzegovina	0.157	43	6	11.2	17.5	86.2	96.2	42.2	62.1
	High human development									
75	Iran (Islamic Republic of)	0.482	123	22	26.2	5.6	59.1	69.5	13.6	67.5
76	Saint Vincent and the Grenadines	..	..	62	42.3	18.2	46.3 [f]	41.5 [f]	..	..
76	Thailand	0.288	73	29	26.1	16.0	51.9	56.7	60.6	76.6
78	China	0.132	41	23	5.2	26.5	68.3 [c]	77.9 [c]	54.6	75.6
79	Peru	0.340	83	69	43.6	38.8	65.9	73.9	65.1	80.5
80	Grenada	0.226	58	21	29.1	31.0	55.4 [d]	50.8 [d]	49.1	63.3
81	Azerbaijan	0.315	80	41	34.8	18.6	98.0	98.4	61.9	69.6
81	Mexico	0.358	88	59	60.1	50.1	65.3	67.0	46.2	76.4
83	Colombia	0.393	98	75	59.5	29.4	62.2	59.8	52.0	76.5
84	Brazil	0.390	96	72	42.7	17.7	70.0	67.6	53.1	73.1
84	Palau	..	..	..	29.9	6.9	96.2 [c]	92.9 [c]	60.5	73.7
86	Moldova (Republic of)	0.146	42	12	23.0	38.6	98.0	98.7	70.1	71.7
87	Ukraine	..	..	17	11.4	20.4	..	..	47.4	62.3
88	Ecuador	0.358	88	66	55.5	43.1	54.2	54.3	52.9	77.3
89	Dominican Republic	0.417	106	107	52.8	25.7	62.3	58.7	52.8	76.9
89	Guyana	0.427	109	112	69.9	36.6	59.4 [e]	57.7 [e]	39.7	61.8
89	Sri Lanka	0.367	93	29	15.1	5.3	81.1	83.1	32.0	70.5
92	Tonga	0.444	115	126	24.8	7.1	94.2	94.1	53.3	71.4
93	Maldives	0.309	79	57	5.4	4.6	48.6 [e]	47.7 [e]	55.4	78.8
93	Viet Nam	0.299	78	46	34.3	30.3	61.5	70.0	67.9	76.7
95	Turkmenistan	..	..	5	21.2	25.6	98.1 [c]	98.3 [c]	..	..
96	Algeria	0.443	114	78	8.7	6.8	47.0 [c]	51.3 [c]	17.6	65.5
97	Cuba	0.296	75	39	48.7	55.7	78.5 [c]	81.6 [c]	57.3	84.7
98	Dominica	..	..	..	34.1	37.5	57.9	64.9	..	..
99	Paraguay	0.412	104	71	70.3	23.2	57.5	56.9	59.2	82.8
100	Egypt	0.398	101	17	41.8	22.9	62.5 [e]	70.2 [e]	15.0	69.2
100	Jordan	0.433	111	41	18.4	13.3	73.8	85.8	13.8	60.5
102	Lebanon	0.360	91	21	20.8	6.3	64.1 [g]	65.9 [g]	30.5	70.3
103	Saint Lucia	0.327	82	73	27.8	24.1	50.2 [c]	44.2 [c]	62.7	75.8
104	Mongolia	0.284	72	39	19.7	17.1	94.2	92.7	52.8	68.9
105	Tunisia	0.238	62	37	4.3	16.2	38.9	45.5	26.7	64.9
106	South Africa	0.388	95	127	51.6	45.7 [h]	77.0	78.7	49.0	61.4
107	Uzbekistan	0.291	74	30	34.1	30.0	100.0	100.0	43.6	72.0
108	Bolivia (Plurinational State of)	0.419	107	161	64.8	48.2	57.4	67.8	72.6	84.5
108	Gabon	0.505	135	227	91.7	23.8	71.6	56.9	39.7	57.4
108	Marshall Islands	..	..	..	71.8	12.1	96.3 [c]	97.1 [c]	42.7	60.8
111	Botswana	0.490	127	186	53.8	11.1	71.4	72.6	63.1	73.1
111	Fiji	0.350	85	38	21.2	10.9	87.9 [i]	86.7 [i]	38.4	75.8
113	Indonesia	0.423	108	173	26.4	21.6	53.5	59.9	53.4	82.2
114	Suriname	0.391	97	96	48.0	29.4	45.5 [j]	42.3 [j]	47.8	66.8
115	Belize	0.428	110	130	55.2	23.9	57.5 [c]	52.0 [c]	65.4	84.9
115	Libya	0.253	65	72	5.9	16.5	62.2 [k]	45.3 [k]	33.2	60.3
117	Jamaica	0.358	88	99	36.5	31.0	79.8	74.3	60.6	72.4
117	Kyrgyzstan	0.340	83	50	28.3	20.0	91.2 [c]	93.6 [c]	45.9	74.7
117	Philippines	0.351	86	78	31.9	27.5	63.6	60.0	50.2	72.5

Continued →

HDI RANK		Gender Inequality Index		SDG 3.1 Maternal mortality ratio	SDG 3.7 Adolescent birth rate	SDG 5.5 Share of seats in parliament	SDG 4.4 Population with at least some secondary education (% ages 25 and older)		Labour force participation rate[a] (% ages 15 and older)	
		Value	Rank	(deaths per 100,000 live births)	(births per 1,000 women ages 15–19)	(% held by women)	Female	Male	Female	Male
		2023	2023	2020	2023	2023	2023[b]	2023[b]	2023	2023
120	Morocco	0.438	113	72	25.1	21.4	33.0	38.8	19.8	69.6
121	Venezuela (Bolivarian Republic of)	0.512	137	259	73.3	22.2[l]	77.0[e]	72.4[e]	47.2	71.8
122	Samoa	0.416	105	59	43.5	13.0	94.4	90.0	31.4	56.6
123	Nicaragua	0.408	103	78	93.5	51.6	60.5	63.1	51.2	82.3
124	Nauru	..	..	..	76.2	10.5	..	..	56.9	72.7
Medium human development										
125	Bhutan	0.278	71	60	9.4	15.5	26.7[k]	34.3[k]	56.8	72.4
126	Eswatini (Kingdom of)	0.484	124	240	68.7	25.0	45.8	53.0	47.1	52.3
126	Iraq	0.558	148	76	58.0	29.1	24.5	39.8	10.7	67.2
128	Tajikistan	0.258	68	17	40.4	26.6	93.7[m]	93.6[e]	34.4	52.7
129	Tuvalu	..	..	..	27.5	6.3	61.1[c]	60.6[c]	35.2	52.4
130	Bangladesh	0.487	125	123	73.2	20.9	43.2	48.0	43.4	80.8
130	India	0.403	102	103	14.1	14.8	43.5	61.1	35.1	76.4
132	El Salvador	0.362	92	43	54.2	27.4	46.4	52.8	48.8	78.1
133	Equatorial Guinea	..	..	212	150.4	27.0	..	..	..	..
133	Palestine, State of	..	..	20	36.0	..	70.6	68.3	18.6	70.7
135	Cabo Verde	0.298	77	42	38.8	41.7	30.2[f]	34.8[f]	44.9	61.9
136	Namibia	0.448	116	215	66.0	35.6	73.3[c]	70.7[c]	55.3	60.7
137	Guatemala	0.480	121	96	68.3	20.0	29.9	35.9	39.7	82.2
138	Congo	0.565	151	282	109.9	20.2	32.5[e]	50.6[e]	44.6	65.0
139	Honduras	0.437	112	72	82.1	27.3	30.0	28.6	40.3	75.4
140	Kiribati	..	..	76	44.0	6.7	..	..	43.0	54.8
141	Sao Tome and Principe	0.492	130	146	86.2	14.5	42.6[n]	52.5[n]	25.7	25.9
142	Timor-Leste	0.394	99	204	27.4	36.9	35.3	40.9	40.9	52.5
143	Ghana	0.514	138	263	58.2	14.5	45.6	65.1	62.1	65.5
143	Kenya	0.526	143	530	56.3	24.6	60.5	70.1	62.8	72.4
145	Nepal	0.487	125	174	67.2	33.2	26.6	43.2	33.1	56.1
146	Vanuatu	0.556	147	94	66.2	1.9	46.6[c]	48.2[c]	43.1	48.8
147	Lao People's Democratic Republic	0.475	117	126	81.7	22.0	19.3[e]	31.0[e]	61.5	70.8
148	Angola	0.515	139	222	140.8	39.1	29.0	52.3	75.6	78.7
149	Micronesia (Federated States of)	..	..	74	43.7	14.3	..	..	48.6	68.1
150	Myanmar	0.478	118	179	33.5	15.0[l]	38.5[g]	47.8[g]	43.6	76.7
151	Cambodia	0.506	136	218	46.9	14.4	16.4	29.0	70.5	83.8
152	Comoros	0.501	132	217	55.2	16.7	27.3	36.3	49.3	64.5
153	Zimbabwe	0.519	140	357	98.1	34.0	88.8	92.9	62.1	74.4
154	Zambia	0.524	141	135	115.9	15.0	35.5[e]	52.9[e]	56.4	67.8
155	Cameroon	0.558	148	438	106.7	32.9	25.0[e]	39.4[e]	56.3	74.0
156	Solomon Islands	0.478	118	122	50.4	8.0	38.2[o]	47.8[o]	87.1	87.7
157	Côte d'Ivoire	0.589	159	480	92.1	16.8	20.0	32.7	59.6	75.5
157	Uganda	0.524	141	284	107.0	33.8	24.6[c]	40.4[c]	74.5	85.8
159	Rwanda	0.394	99	259	30.8	54.7	20.5	24.5	58.1	69.9
160	Papua New Guinea	0.584	156	192	54.1	2.7	27.4	41.3	50.7	53.3
161	Togo	0.564	150	399	77.1	19.8	14.3[c]	33.3[c]	69.1	72.7
162	Syrian Arab Republic	0.490	127	30	38.9	10.8	24.1[k]	32.0[k]	14.7	69.8
163	Mauritania	0.603	161	464	88.9	23.3	16.7[e]	27.9[e]	31.6	66.6
164	Nigeria	0.677	171	1,047	86.4	3.6	42.4	57.8	80.7	84.5
165	Tanzania (United Republic of)	0.504	134	238	113.2	37.4	12.6	18.3	74.9	84.0
166	Haiti	0.618	165	350	49.8	2.7[p]	27.0[i]	36.0[i]	50.1	65.6
167	Lesotho	0.534	144	566	70.6	26.0	35.3[c]	30.6[c]	53.6	63.9
Low human development										
168	Pakistan	0.536	145	154	41.1	20.1	27.8	48.4	25.0	81.1
169	Senegal	0.490	127	261	60.2	46.1	15.4	24.8	39.2	68.7
170	Gambia	0.578	154	458	58.1	8.6	35.5	49.5	45.4	50.1
171	Congo (Democratic Republic of the)	0.604	162	547	106.9	14.8	40.8[c]	66.7[c]	59.7	66.0
172	Malawi	0.581	155	381	113.6	20.7	13.4[e]	26.9[e]	63.8	74.9
173	Benin	0.573	153	523	77.8	26.6	7.2	21.0	74.7	78.0
174	Guinea-Bissau	0.632	166	725	82.0	9.8	27.3	50.6	60.1	70.2
175	Djibouti	0.481	122	234	19.0	26.2	16.7[f]	34.1[f]	19.0	48.4
176	Sudan	0.588	158	270	66.1	31.0[q]	22.5	26.9	14.4	61.9
177	Liberia	0.646	167	652	126.0	10.7	24.0[c]	46.5[c]	46.0	52.8

Continued →

HDI RANK		Gender Inequality Index		SDG 3.1 Maternal mortality ratio (deaths per 100,000 live births)	SDG 3.7 Adolescent birth rate (births per 1,000 women ages 15–19)	SDG 5.5 Share of seats in parliament (% held by women)	SDG 4.4 Population with at least some secondary education (% ages 25 and older)		Labour force participation rate[a] (% ages 15 and older)	
		Value	Rank				Female	Male	Female	Male
		2023	2023	2020	2023	2023	2023[b]	2023[b]	2023	2023
178	Eritrea	..	..	322	65.2	22.0[p]	..	..	..	..
179	Guinea	0.609	163	553	118.6	29.6	8.1[c]	21.1[c]	47.0	68.2
180	Ethiopia	0.497	131	267	69.9	38.8	7.4[c]	12.7[c]	55.6	78.1
181	Afghanistan	0.661	168	620	64.1	27.2[l]	7.0	24.1	24.5	88.6
182	Mozambique	0.479	120	127	153.5	43.2	13.2	23.7	76.6	82.4
183	Madagascar	0.584	156	392	129.8	17.2	15.9	21.2	68.9	81.6
184	Yemen	0.838	172	183	75.3	0.3	20.7	47.2	5.9	65.7
185	Sierra Leone	0.566	152	443	93.6	28.2	14.7[c]	34.4[c]	50.2	56.3
186	Burkina Faso	0.555	146	264	87.1	16.9	7.3	13.0	41.8	54.5
187	Burundi	0.501	132	494	53.4	38.9	8.6[c]	14.5[c]	77.7	79.3
188	Mali	0.612	164	440	138.6	28.6	8.2[c]	16.4[c]	41.9	77.7
188	Niger	0.591	160	441	145.3	25.9[r]	6.1	11.5	73.4	87.3
190	Chad	0.670	169	1,063	134.7	25.9	3.7[g]	15.1[g]	52.4	76.8
191	Central African Republic	..	..	835	163.1	12.9	14.6	32.0	..	..
192	Somalia	0.675	170	621	117.1	20.7	4.4	17.8	22.2	49.5
193	South Sudan	..	..	1,223	97.1	32.3	26.5[s]	36.4[s]	..	..
Other countries or territories										
	Korea (Democratic People's Rep. of)	..	..	107	0.5	17.6	84.1	93.7	..	..
	Monaco	..	..	..	9.7	45.8	..	..	39.9	56.9
Human development groups										
	Very high human development	0.125	–	14	10.1	30.2	90.8	92.7	54.1	69.3
	High human development	0.334	–	67	25.5	25.6	65.7	72.2	50.4	74.8
	Medium human development	0.513	–	291	44.8	22.5	41.1	56.5	43.4	76.6
	Low human development	0.571	–	369	81.5	25.3	19.8	34.9	41.7	75.1
Developing countries		0.478	–	236	42.9	24.6	53.9	64.2	46.9	75.5
Regions										
	Arab States	0.539	–	133	44.2	17.8	45.8	56.9	18.4	69.8
	East Asia and the Pacific	0.315	–	78	15.5	21.7	64.6	73.2	55.0	76.4
	Europe and Central Asia	0.226	–	21	19.5	26.0	82.3	90.3	45.7	69.3
	Latin America and the Caribbean	0.384	–	85	51.4	34.2	66.2	66.1	51.8	75.1
	South Asia	0.458	–	132	26.1	17.9	42.5	58.9	33.5	76.7
	Sub-Saharan Africa	0.558	–	509	94.2	27.3	32.1	43.8	64.3	75.6
Least developed countries		0.552	–	352	90.6	25.6	24.3	35.2	51.0	75.0
Small island developing states		0.451	–	203	46.9	26.2	57.8	61.9	54.1	71.0
Organisation for Economic Co-operation and Development		0.192	–	22	17.5	33.1	88.0	90.6	53.5	68.7
World		**0.455**	**–**	**216**	**39.1**	**26.5**	**62.0**	**70.2**	**48.5**	**74.1**

Notes

a	Updated by HDRO based on data from International Labour Organization (2024).
b	Data refer to 2023 or the most recent year available.
c	Updated by HDRO based on data from UNESCO Institute for Statistics (2024).
d	Refers to 2020 based on UNESCO Institute for Statistics (2024).
e	Updated by HDRO based on data from Barro and Lee (2018) and UNESCO Institute for Statistics (2024).
f	Updated by HDRO based on data from UNESCO Institute for Statistics (2024) and estimates using cross-country regression.
g	Refers to 2019 based on UNESCO Institute for Statistics (2024).
h	Excludes the 36 special rotating delegates appointed on an ad hoc basis.
i	Refers to 2017 based on UNESCO Institute for Statistics (2024).
j	Refers to 2018 based on UNESCO Institute for Statistics (2024).
k	HDRO estimate based on data from Robert Barro and Jong-Wha Lee, ICF Macro Demographic and Health Surveys, the Organisation for Economic Co-operation and Development, the United Nations Educational, Scientific and Cultural Organization (UNESCO) Institute for Statistics and United Nations Children's Fund (UNICEF) Multiple Indicator Cluster Surveys.
l	Refers to 2021.
m	HDRO estimate based on data from Barro and Lee (2018), UNESCO Institute for Statistics (2024) and UNICEF Multiple Indicator Cluster Surveys.
n	Updated by HDRO based on data from UNESCO Institute for Statistics (2024) and UNICEF Multiple Indicator Cluster Surveys for various years.
o	Refers to 2013 based on UNESCO Institute for Statistics (2024).
p	Refers to 2019.
q	Refers to 2018.
r	Refers to 2022.
s	Refers to 2008 based on UNESCO Institute for Statistics (2024).

Definitions

Gender Inequality Index: A composite measure reflecting inequality in achievement between women and men in three dimensions: reproductive health, empowerment and the labour market. See *Technical note 4* at https://hdr.undp.org/sites/default/files/2025_HDR/hdr2025_technical_notes.pdf for details on how the Gender Inequality Index is calculated.

Maternal mortality ratio: Number of deaths due to pregnancy-related causes per 100,000 live births.

Adolescent birth rate: Number of births to women ages 15–19 per 1,000 women ages 15–19.

Share of seats in parliament: Proportion of seats held by women in the national parliament expressed as a percentage of total seats. For countries with a bicameral legislative system, the share of seats is calculated based on both houses.

Population with at least some secondary education: Percentage of the population ages 25 and older that has reached (but not necessarily completed) a secondary level of education.

Labour force participation rate: Proportion of the working-age population (ages 15 and older) that engages in the labour market, either by working or actively looking for work, expressed as a percentage of the working-age population.

Main data sources

Column 1: HDRO calculations based on data in columns 3–9.

Column 2: Calculated based on data in column 1.

Column 3: WHO, UNICEF, UNFPA, World Bank Group and UNDESA/Population Division 2023.

Column 4: UNDESA 2024a.

Column 5: IPU 2024.

Columns 6 and 7: Barro and Lee 2018, UNESCO Institute for Statistics 2024 and UNICEF Multiple Indicator Cluster Surveys.

Columns 8 and 9: ILO 2024.

TABLE 6

Multidimensional Poverty Index: developing countries

Country	Multidimensional Poverty Index[a]: Year and survey[b] 2012-2023	Multidimensional Poverty Index[a]: Value	Population in multidimensional poverty[a]: Headcount (%) SDG 1.2	Population in multidimensional poverty[a]: Headcount (thousands) In survey year	Population in multidimensional poverty[a]: Headcount (thousands) 2022	Population in multidimensional poverty[a]: Intensity of deprivation (%)	Population in multidimensional poverty[a]: Inequality among the poor Value	Population in severe multidimensional poverty (%)	Population vulnerable to multidimensional poverty[a] (%)	Contribution of deprivation in dimension to overall multidimensional poverty[a]: Health (%)	Contribution of deprivation in dimension to overall multidimensional poverty[a]: Education (%)	Contribution of deprivation in dimension to overall multidimensional poverty[a]: Standard of living (%)	Population living below monetary poverty line (%): National poverty line 2012-2023[c] SDG 1.2	Population living below monetary poverty line (%): PPP $2.15 a day 2012-2023[c] SDG 1.1
Estimates based on surveys for 2018–2023														
Afghanistan	2022/2023 M	0.360 [d]	64.9 [d]	26,897 [d]	26,329 [d]	55.5 [d]	0.020 [d]	39.1 [d]	19.9 [d]	24.1 [d]	42.5 [d]	33.4 [d]	54.5	..
Albania	2017/2018 D	0.003	0.7	20	20	39.1	.. [e]	0.1	5.0	28.3	55.1	16.7	22.0	0.0
Algeria	2018/2019 M	0.005	1.4	598	628	39.2	0.007	0.2	3.6	31.2	49.3	19.5	..	..
Argentina	2019/2020 M [f]	0.001 [g]	0.4 [g]	195 [g]	196 [g]	34.0 [g]	.. [e]	0.0 [g]	1.6 [g]	69.7 [g]	21.4 [g]	8.9 [g]	39.2	0.6
Bangladesh	2019 M	0.104	24.6	40,636	41,737	42.2	0.010	6.5	18.2	17.3	37.6	45.1	18.7	5.0
Benin	2021/2022 M	0.290	55.9	7,695	7,695	51.8	0.021	30.8	17.8	18.9	38.8	42.3	38.5	12.7
Bhutan	2022 N	0.039 [g,h]	9.8 [g,h]	76 [g,h]	76 [g,h]	39.4 [g,h]	0.008 [g,h]	1.6 [g,h]	8.3 [g,h]	65.4 [g,h]	17.5 [g,h]	17.1 [g,h]	12.4	0.0
Burkina Faso	2021 D	0.343	64.5	14,181	14,513	53.2	0.022	38.3	15.8	19.6	39.2	41.1	43.2	25.3
Cambodia	2021/2022 D	0.070	16.6	2,863	2,863	42.3	0.009	4.1	20.5	21.5	48.0	30.5	17.7	..
Cameroon	2018 D	0.232	43.6	10,814	12,046	53.2	0.026	24.6	17.6	25.2	27.6	47.1	37.5	23.0
Central African Republic	2018/2019 M	0.461	80.4	3,976	4,100	57.4	0.025	55.8	12.9	20.2	27.8	52.0	68.8	65.7
Chad	2019 M	0.517	84.2	14,045	15,535	61.4	0.024	64.6	10.7	19.1	36.6	44.3	42.3	30.8
Comoros	2022 M	0.084	19.2	160	160	43.9	0.013	5.7	19.4	22.7	34.4	42.9	42.4	18.6
Congo (Democratic Republic of the)	2017/2018 M	0.331	64.5	58,097	66,064	51.3	0.020	36.8	17.4	23.1	19.9	57.0	63.9	78.9
Costa Rica	2018 M	0.002 [d,g]	0.5 [d,g]	27 [d,g]	27 [d,g]	37.1 [d,g]	.. [e]	0.0 [d,g]	2.4 [d,g]	40.5 [d,g]	41.0 [d,g]	18.5 [d,g]	25.5	0.9
Côte d'Ivoire	2021 D	0.210	42.8	12,678	13,001	49.1	0.018	19.7	19.6	21.3	42.1	36.6	37.5	9.7
Cuba	2019 M	0.003 [g]	0.7 [g]	79 [g]	78 [g]	38.1 [g]	.. [e]	0.1 [g]	2.7 [g]	10.1 [g]	39.8 [g]	50.1 [g]	..	..
Dominican Republic	2019 M	0.009	2.3	247	255	38.8	0.006	0.2	4.8	14.6	46.2	39.2	23.9	0.8
Ecuador	2018 N	0.008	2.1	357	373	38.0	0.004	0.1	5.9	33.9	27.3	38.8	25.2	3.2
Eswatini (Kingdom of)	2021/2022 M	0.033 [d]	7.9 [d]	96 [d]	96 [d]	41.3 [d]	0.008 [d]	1.3 [d]	19.0 [d]	31.1 [d]	28.6 [d]	40.3 [d]	58.9	36.1
Ethiopia	2019 D	0.367	68.7	79,554	86,185	53.3	0.022	41.9	18.4	14.0	31.5	54.5	23.5	27.0
Fiji	2021 M	0.006	1.5	14	14	38.1	.. [e]	0.2	7.4	38.0	17.4	44.6	24.1	1.3
Gabon	2019/2021 D	0.037	8.6	206	210	42.4	0.010	2.3	14.9	34.6	24.4	41.0	33.4	2.5
Gambia	2019/2020 D	0.198	41.7	1,049	1,100	47.5	0.016	17.3	28.0	32.7	33.0	34.3	53.4	17.2
Georgia	2018 M	0.001 [g]	0.3 [g]	13 [g]	13 [g]	36.6 [g]	.. [e]	0.0 [g]	2.1 [g]	47.1 [g]	23.8 [g]	29.1 [g]	15.6	5.5
Ghana	2022 D	0.113	24.8	8,221	8,221	45.5	0.016	8.4	20.0	25.1	28.9	46.0	23.4	25.2
Guinea	2018 D	0.373	66.2	8,412	9,306	56.4	0.025	43.5	16.4	21.4	38.4	40.3	43.7	13.8
Guinea-Bissau	2018/2019 M	0.341	64.4	1,267	1,356	52.9	0.021	35.9	20.0	19.1	35.0	45.8	47.7	26.0
Guyana	2019/2020 M	0.007 [i]	1.8 [i]	15 [i]	15 [i]	39.3 [i]	0.007 [i]	0.2 [i]	6.5 [i]	30.4 [i]	22.4 [i]	47.2 [i]	..	..
Honduras	2019 M	0.051	12.0	1,191	1,253	42.7	0.011	3.0	14.8	18.8	39.2	42.0	48.0	12.7
India	2019/2021 D	0.069	16.4	231,828	233,667	42.0	0.010	4.2	18.7	32.2	28.2	39.7	..	12.9
Iraq	2018 M	0.033	8.6	3,477	3,806	37.9	0.005	1.3	5.2	33.1	60.9	6.0	18.9	0.1
Jamaica	2018 N	0.011 [j]	2.8 [j]	78 [j]	79 [j]	38.9 [j]	0.005 [j]	0.2 [j]	5.0 [j]	52.2 [j]	20.9 [j]	26.9 [j]	19.9	0.3
Jordan	2017/2018 D	0.002	0.4	45	49	35.4	.. [e]	0.0	0.7	37.5	53.5	9.0	15.7	..
Kenya	2022 D	0.113	25.4	13,754	13,754	44.7	0.015	7.5	26.4	25.6	15.6	58.8	36.1	36.1
Kiribati	2018/2019 M	0.080	19.8	25	26	40.5	0.006	3.5	30.2	30.3	12.1	57.6	21.9	1.7
Kyrgyzstan	2018 M	0.001	0.4	25	27	36.3	.. [e]	0.0	5.2	64.6	17.9	17.5	33.3	0.7
Lesotho	2018 M	0.084 [d]	19.6 [d]	428 [d]	448 [d]	43.0 [d]	0.009 [d]	5.0 [d]	28.6 [d]	21.9 [d]	18.1 [d]	60.0 [d]	49.7	32.4
Liberia	2019/2020 D	0.259	52.3	2,694	2,811	49.6	0.018	24.9	23.3	19.7	28.6	51.7	50.9	27.6
Madagascar	2021 D	0.386	68.4	20,314	20,825	56.4	0.026	45.8	15.4	17.8	31.6	50.6	70.7	80.7
Malawi	2019/2020 M	0.231	49.9	9,744	10,260	46.3	0.012	17.5	27.5	18.6	25.5	55.9	50.7	70.1
Mali	2018 D	0.376	68.3	13,968	15,766	55.0	0.022	44.7	15.3	19.6	41.2	39.3	44.6	20.8
Mauritania	2019/2021 D	0.327	58.4	2,767	2,850	56.0	0.024	38.0	12.3	17.7	42.4	39.9	31.8	5.4
Mexico	2022 N	0.020 [k,l]	5.0 [k,l]	6,434 [k,l]	6,434 [k,l]	39.8 [k,l]	0.006 [k,l]	0.9 [k,l]	3.1 [k,l]	62.7 [k,l]	12.8 [k,l]	24.4 [k,l]	36.3	1.2
Mongolia	2018 M	0.028 [m]	7.3 [m]	230 [m]	246 [m]	38.8 [m]	0.004 [m]	0.8 [m]	15.5 [m]	21.1 [m]	26.8 [m]	52.1 [m]	27.8	0.2
Montenegro	2018 M	0.005	1.2	8	8	39.6	.. [e]	0.1	2.9	58.5	22.3	19.2	20.3	2.0
Morocco	2017/2018 P	0.027 [n]	6.4 [n]	2,279 [n]	2,374 [n]	42.0 [n]	0.012 [n]	1.4 [n]	10.9 [n]	24.4 [n]	46.8 [n]	28.8 [n]	4.8	1.4
Mozambique	2022/2023 D	0.334	60.7	20,407	19,813	55.1	0.022	38.8	16.9	17.3	33.2	49.5	46.1	74.5
Nepal	2022 D	0.085	20.1	5,963	5,963	42.5	0.011	5.5	20.2	28.8	30.6	40.6	..	..
Nigeria	2021 M	0.175 [h,o]	33.0 [h,o]	72,211 [h,o]	73,738 [h,o]	52.9 [h,o]	0.027 [h,o]	18.1 [h,o]	16.6 [h,o]	19.5 [h,o]	35.5 [h,o]	45.0 [h,o]	40.1	30.9
North Macedonia	2018/2019 M	0.001	0.4	7	7	38.2	.. [e]	0.1	2.2	29.6	52.6	17.8	21.8	2.7
Pakistan	2017/2018 D	0.198	38.3	86,987	93,416	51.7	0.023	21.5	12.9	27.6	41.3	31.1	21.9	4.9
Palestine, State of	2019/2020 M	0.002	0.6	29	30	35.0	.. [e]	0.0	1.3	62.9	31.0	6.1	29.2	0.5
Papua New Guinea	2016/2018 D	0.263 [h]	56.6 [h]	5,320 [h]	5,778 [h]	46.5 [h]	0.016 [h]	25.8 [h]	25.3 [h]	4.6 [h]	30.1 [h]	65.3 [h]	..	..
Peru	2022 N	0.025	6.4	2,136	2,136	38.9	0.006	0.9	10.0	15.5	32.7	51.9	27.5	2.7
Philippines	2022 D	0.016 [h]	3.9 [h]	4,429 [h]	4,429 [h]	40.6 [h]	0.008 [h]	0.7 [h]	5.2 [h]	24.6 [h]	32.7 [h]	42.7 [h]	18.1	3.0
Rwanda	2019/2020 D	0.231	48.8	6,379	6,665	47.3	0.014	19.7	22.7	19.0	26.6	54.4	38.2	52.0
Samoa	2019/2020 M	0.025	6.3	13	14	39.1	0.003	0.5	12.9	36.9	31.2	31.9	21.9	1.2
Sao Tome and Principe	2019 M	0.048	11.7	25	27	40.9	0.007	2.1	17.0	18.7	36.6	44.6	55.5	15.7
Senegal	2019 D	0.263	50.8	8,313	8,972	51.7	0.019	27.7	18.2	20.7	48.4	30.9	..	9.9

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	Multidimensional Poverty Index[a]		SDG 1.2 Population in multidimensional poverty[a]							Contribution of deprivation in dimension to overall multidimensional poverty[a]			SDG 1.2 Population living below monetary poverty line (%)	SDG 1.1 Population living below monetary poverty line (%)
	Year and survey[b]		Headcount	Headcount (thousands)		Intensity of deprivation	Inequality among the poor	Population in severe multidimensional poverty	Population vulnerable to multidimensional poverty[a]	Health	Education	Standard of living	National poverty line	PPP $2.15 a day
Country	2012–2023	Value	(%)	In survey year	2022	(%)	Value	(%)	(%)	(%)	(%)	(%)	2012–2023[c]	2012–2023[c]
Serbia	2019 M	0.000 [g,p]	0.1 [g,p]	8 [g,p]	8 [g,p]	38.1 [g,p]	.. [e]	0.0 [g,p]	2.1 [g,p]	30.9 [g,p]	40.1 [g,p]	29.0 [g,p]	20.0	1.2
Seychelles	2019 N	0.003 [d,q]	0.9 [d,q]	1 [d,q]	1 [d,q]	34.2 [d,q]	.. [e]	0.0 [d,q]	0.4 [d,q]	66.8 [d,q]	32.1 [d,q]	1.1 [d,q]	25.3	0.5
Sierra Leone	2019 D	0.293	59.2	4,579	4,902	49.5	0.019	28.0	21.3	23.0	24.1	53.0	56.8	26.1
Suriname	2018 M	0.011	2.9	17	18	39.4	0.007	0.4	4.0	20.4	43.8	35.8	..	1.1
Tanzania (United Republic of)	2022 D	0.221	47.2	30,554	30,554	46.9	0.014	18.3	23.1	24.2	22.6	53.2	26.4	44.9
Thailand	2022 M	0.002 [g]	0.5 [g]	352 [g]	352 [g]	37.0 [g]	0.003 [g]	0.0 [g]	4.7 [g]	31.2 [g]	54.0 [g]	14.7 [g]	6.3	0.0
Tonga	2019 M	0.003	0.9	1	1	38.1	.. [e]	0.0	6.4	38.2	40.7	21.1	20.6	0.0
Trinidad and Tobago	2022 M	0.002 [h]	0.5 [h]	8 [h]	8 [h]	38.8 [h]	0.005 [h]	0.1 [h]	0.8 [h]	64.2 [h]	23.7 [h]	12.1 [h]	..	..
Tunisia	2023 M	0.003	1.0	119	118	35.2	0.002	0.0	2.8	28.1	61.8	10.1	16.6	0.3
Turkmenistan	2019 M	0.001 [d]	0.2 [d]	17 [d]	18 [d]	34.0 [d]	.. [e]	0.0 [d]	0.3 [d]	82.4 [d]	15.5 [d]	2.1 [d]	..	..
Tuvalu	2019/2020 M	0.008	2.1	0	0	38.2	0.002	0.0	12.2	36.5	43.6	20.0	..	..
Uzbekistan	2021/2022 M	0.006 [h,r]	1.7 [h,r]	604 [h,r]	604 [h,r]	35.3 [h,r]	0.001 [h,r]	0.0 [h,r]	0.2 [h,r]	94.5 [h,r]	0.0 [h,r]	5.5 [h,r]	14.1	2.3
Viet Nam	2020/2021 M	0.008 [h]	1.9 [h]	1,899 [h]	1,913 [h]	40.3 [h]	0.010 [h]	0.4 [h]	3.5 [h]	22.9 [h]	40.7 [h]	36.4 [h]	4.3	1.0
Yemen	2022/2023 M	0.188 [s]	37.4 [s]	14,740 [s]	14,303 [s]	50.2 [s]	0.019 [s]	17.0 [s]	22.5 [s]	28.4 [s]	31.7 [s]	39.9 [s]	48.6	19.8
Zambia	2018 D	0.232	47.9	8,610	9,654	48.4	0.015	21.0	23.9	21.5	25.0	53.5	60.0	64.3
Zimbabwe	2019 M	0.110	25.8	3,940	4,146	42.6	0.009	6.8	26.3	23.6	17.3	59.2	38.3	39.8
Estimates based on surveys for 2012–2017														
Angola	2015/2016 D	0.282	51.1	14,914	18,211	55.3	0.024	32.5	15.5	21.2	32.1	46.8	32.3	31.1
Armenia	2015/2016 D	0.001 [t]	0.2 [t]	6 [t]	5 [t]	36.2 [t]	.. [e]	0.0 [t]	2.8 [t]	33.1 [t]	36.8 [t]	30.1 [t]	24.8	0.8
Barbados	2012 M	0.009 [j]	2.5 [j]	7 [j]	7 [j]	34.2 [j]	.. [e]	0.0 [j]	0.5 [j]	96.0 [j]	0.7 [j]	3.3 [j]	..	..
Belize	2015/2016 M	0.017	4.3	16	17	39.8	0.007	0.6	8.4	39.5	20.9	39.6	..	..
Bolivia (Plurinational State of)	2016 N	0.038	9.1	1,013	1,094	41.7	0.008	1.9	12.1	18.7	31.5	49.8	36.4	2.0
Bosnia and Herzegovina	2011/2012 M	0.008 [j]	2.2 [j]	80 [j]	70 [j]	37.9 [j]	0.002 [j]	0.1 [j]	4.1 [j]	79.7 [j]	7.2 [j]	13.1 [j]	16.9	..
Botswana	2015/2016 N	0.073 [u]	17.2 [u]	385 [u]	420 [u]	42.2 [u]	0.008 [u]	3.5 [u]	19.7 [u]	30.3 [u]	16.5 [u]	53.2 [u]	16.1	15.4
Brazil	2015 N [v]	0.016 [g,h,v]	3.8 [g,h,v]	7,748 [g,h,v]	8,080 [g,h,v]	42.5 [g,h,v]	0.008 [g,h,v]	0.9 [g,h,v]	6.2 [g,h,v]	49.8 [g,h,v]	22.9 [g,h,v]	27.3 [g,h,v]	..	3.5
Burundi	2016/2017 D	0.409 [t]	75.1 [t]	8,641 [t]	10,004 [t]	54.4 [t]	0.022 [t]	46.1 [t]	15.8 [t]	23.8 [t]	27.2 [t]	49.0 [t]	64.9	62.1
China	2014 N [w]	0.016 [s,x]	3.9 [s,x]	53,922 [s,x]	55,369 [s,x]	41.4 [s,x]	0.005 [s,x]	0.3 [s,x]	17.4 [s,x]	35.2 [s,x]	39.2 [s,x]	25.6 [s,x]	0.0	0.1
Colombia	2015/2016 D	0.020 [h]	4.8 [h]	2,299 [h]	2,507 [h]	40.6 [h]	0.009 [h]	0.8 [h]	6.2 [h]	12.0 [h]	39.5 [h]	48.5 [h]	36.6	6.0
Congo	2014/2015 M	0.112	24.3	1,237	1,465	46.0	0.013	9.4	21.3	23.4	20.2	56.4	..	..
Egypt	2014 D	0.020 [d,t]	5.2 [d,t]	5,109 [d,t]	5,900 [d,t]	37.6 [d,t]	0.004 [d,t]	0.6 [d,t]	6.1 [d,t]	40.0 [d,t]	53.1 [d,t]	6.9 [d,t]	29.7	1.5
El Salvador	2014 M	0.032	7.9	484	494	41.3	0.009	1.7	9.9	15.5	43.4	41.1	26.6	3.4
Guatemala	2014/2015 D	0.134	28.9	4,613	5,155	46.2	0.013	11.2	21.1	26.3	35.0	38.7	59.3	9.5
Haiti	2016/2017 D	0.200	41.3	4,464	4,747	48.4	0.019	18.5	21.8	18.5	24.6	57.0	58.5	29.2
Indonesia	2017 D	0.014 [h]	3.6 [h]	9,675 [h]	10,091 [h]	38.7 [h]	0.006 [h]	0.4 [h]	4.7 [h]	34.7 [h]	26.8 [h]	38.5 [h]	9.4	1.9
Kazakhstan	2015 M	0.002 [g,t]	0.5 [g,t]	82 [g,t]	91 [g,t]	35.6 [g,t]	.. [e]	0.0 [g,t]	1.8 [g,t]	90.4 [g,t]	3.1 [g,t]	6.4 [g,t]	5.2	0.0
Lao People's Democratic Republic	2017 M	0.108	23.1	1,619	1,744	47.0	0.016	9.6	21.2	21.5	39.7	38.8	18.3	7.1
Libya	2014 P	0.007	2.0	128	144	37.1	0.003	0.1	11.4	39.0	48.6	12.4	..	..
Maldives	2016/2017 D	0.003	0.8	4	4	34.4	.. [e]	0.0	4.8	80.7	15.1	4.2	5.4	0.0
Moldova (Republic of)	2012 M	0.004	0.9	33	29	37.4	.. [e]	0.1	3.7	9.2	42.4	48.4	31.1	0.0
Myanmar	2015/2016 D	0.176	38.3	19,731	20,597	45.9	0.015	13.8	21.9	18.5	32.3	49.2	24.8	2.0
Namibia	2013 D	0.185 [t]	40.9 [t]	921 [t]	1,181 [t]	45.2 [t]	0.013 [t]	13.1 [t]	19.2 [t]	31.6 [t]	13.9 [t]	54.4 [t]	17.4	15.6
Nicaragua	2011/2012 D	0.074 [t]	16.5 [t]	971 [t]	1,108 [t]	45.3 [t]	0.013 [t]	5.6 [t]	13.4 [t]	11.5 [t]	36.2 [t]	52.3 [t]	24.9	3.9
Niger	2012 D	0.601 [t]	91.0 [t]	16,226 [t]	23,027 [t]	66.1 [t]	0.026 [t]	76.3 [t]	4.9 [t]	21.4 [t]	36.7 [t]	41.8 [t]	40.8	50.6
Paraguay	2016 M	0.019	4.5	281	304	41.9	0.013	1.0	7.2	14.3	38.9	46.8	24.7	1.3
Saint Lucia	2012 M	0.007 [j]	1.9 [j]	3 [j]	3 [j]	37.5 [j]	.. [e]	0.0 [j]	1.6 [j]	69.5 [j]	7.5 [j]	23.0 [j]	0.3	0.1
South Africa	2016 D	0.025	6.3	3,583	3,903	39.8	0.005	0.9	12.2	39.5	13.1	47.4	55.5	20.5
Sri Lanka	2016 N	0.011	2.9	640	667	38.3	0.004	0.3	14.3	32.5	24.4	43.0	14.3	1.0
Sudan	2014 M	0.279	52.3	20,315	25,841	53.4	0.023	30.9	17.7	21.1	29.2	49.8	..	15.3
Tajikistan	2017 D	0.029	7.4	676	758	39.0	0.004	0.7	20.1	47.8	26.5	25.8	22.5	6.1
Timor-Leste	2016 D	0.222 [t]	48.3 [t]	593 [t]	661 [t]	45.9 [t]	0.014 [t]	17.4 [t]	26.8 [t]	29.3 [t]	23.1 [t]	47.6 [t]	41.8	24.4
Togo	2017 M	0.180	37.6	3,030	3,419	47.8	0.016	15.2	23.8	20.9	28.1	50.9	45.5	26.6
Uganda	2016 D	0.281 [t]	57.2 [t]	22,181 [t]	27,048 [t]	49.2 [t]	0.017 [t]	25.7 [t]	23.6 [t]	24.0 [t]	21.6 [t]	54.5 [t]	20.3	42.1
Ukraine	2012 M	0.001 [h,t]	0.2 [h,t]	113 [h,t]	100 [h,t]	34.4 [h,t]	.. [e]	0.0 [h,t]	0.4 [h,t]	60.5 [h,t]	28.4 [h,t]	11.2 [h,t]	1.6	0.0
Developing countries	–	0.089	18.3	1,085,191	1,148,746	48.5	0.017	8.0	14.8	24.3	32.0	43.6	19.4	11.5
Regions														
Arab States	–	0.072	14.7	46,840	53,193	48.9	0.018	6.5	9.2	25.7	34.6	39.7	25.9	5.8
East Asia and the Pacific	–	0.021	5.0	100,687	104,097	42.4	0.008	0.9	14.2	28.4	36.0	35.7	3.6	0.6
Europe and Central Asia	–	0.004	1.2	1,692	1,758	37.1	0.003	0.1	2.6	66.7	16.5	16.8	12.0	1.4
Latin America and the Caribbean	–	0.025	5.8	32,683	34,389	42.9	0.010	1.5	6.4	34.3	27.0	38.7	36.2	3.6
South Asia	–	0.094	20.8	393,030	401,859	45.2	0.014	7.3	17.9	28.8	33.8	37.4	23.1	11.0
Sub-Saharan Africa	–	0.254	48.4	510,259	553,451	52.5	0.021	26.9	18.2	20.2	30.4	49.3	40.9	38.6

Notes

a Not all indicators were available for all countries, so caution should be used in cross-country comparisons. When an indicator is missing, weights of available indicators are adjusted to total 100 percent. See *Technical note 5* at https://hdr.undp.org/sites/default/files/2025_HDR/hdr2025_technical_notes.pdf.

b D indicates data from Demographic and Health Surveys, M indicates data from Multiple Indicator Cluster Surveys, N indicates data from national surveys and ˆ indicates data from Pan Arab Population and Family Health Surveys (see https://hdr.undp.org/mpi-2024-faqs and *OPHI Methodological Note 58* at https://ophi.org.uk/publications/MN-58 for the list of national surveys).

c Data refer to the most recent year available during the period specified.

d Missing indicator on cooking fuel.

e Value is not reported because it is based on a small number of multidimensionally poor people.

f Urban areas only.

g Considers child deaths that occurred at any time because the survey did not collect the date of child deaths.

h Missing indicator on nutrition.

i Revised estimate from the 2022 MPI based on the survey microdata update.

j Missing indicator on child mortality.

k Child mortality data were not used because the data were collected from a sample of women ages 15–49 that was not representative of the female population in that age group.

l Anthropometric data were collected from all children under age 5 and from selected individuals who are age 5 or older. Construction of the nutrition indicator was restricted to children under age 5 since the anthropometric sample is representative of the under 5 population.

m Indicator on sanitation follows the national classification in which pit latrine with slab is considered unimproved.

n Following the national report, latrines are considered an improved source for the sanitation indicator.

o The analytical sample was restricted to the Multiple Indicator Cluster Survey sample, and its sample weight was used, because child mortality information was not collected for the National Immunization Coverage Survey sample.

p Because of the high proportion of children excluded from nutrition indicators due to measurements not being taken, estimates based on the 2019 Serbia Multiple Indicator Cluster Survey should be interpreted with caution. The unweighted sample size used for the multidimensional poverty calculation is 82.8 percent.

q Missing indicator on school attendance.

r The analytical sample was restricted to the round 2 sample because standard of living questions were not collected for the round 1 sample.

s Missing indicator on housing.

t Revised estimate from the 2020 MPI.

u Captures only deaths of children under age 5 who died in the last five years and deaths of children ages 12–18 years who died in the last two years.

v The methodology was adjusted to account for the missing indicator on nutrition and the incomplete indicator on child mortality (the survey did not collect the date of child deaths).

w Based on the version of data accessed on 7 June 2016.

x Given the information available in the data, child mortality was constructed based on deaths that occurred between surveys—that is, between 2012 and 2014. Child deaths reported by an adult man in the household were taken into account because the date of death was reported.

Definitions

Multidimensional Poverty Index: Proportion of the population that is multidimensionally poor adjusted by the intensity of the deprivations.

Multidimensional poverty headcount: Population with a deprivation score of at least 33.3 percent. It is expressed as a share of the population in the survey year, the number of multidimensionally poor people in the survey year and the projected number of multidimensionally poor people in 2022.

Intensity of deprivation of multidimensional poverty: Average deprivation score experienced by people in multidimensional poverty.

Inequality among the poor: Variance of individual deprivation scores of poor people. It is calculated by subtracting the deprivation score of each multidimensionally poor person from the intensity, squaring the differences and dividing the sum of the weighted squares by the number of multidimensionally poor people.

Population in severe multidimensional poverty: Percentage of the population in severe multidimensional poverty—that is, those with a deprivation score of 50 percent or more.

Population vulnerable to multidimensional poverty: Percentage of the population at risk of suffering multiple deprivations—that is, those with a deprivation score of 20–33.3 percent.

Contribution of deprivation in dimension to overall multidimensional poverty: Percentage of the Multidimensional Poverty Index attributed to deprivations in each dimension.

Population living below national poverty line: Percentage of the population living below the national poverty line, which is the poverty line deemed appropriate for a country by its authorities. National estimates are based on population-weighted subgroup estimates from household surveys.

Population living below PPP $2.15 a day: Percentage of the population living below the international poverty line of $2.15 (in 2017 purchasing power parity [PPP] terms) a day.

Main data sources

Column 1: Refers to the year and the survey whose data were used to calculate the country's Multidimensional Poverty Index value and its components.

Columns 2–12: HDRO and OPHI calculations based on data on household deprivations in health, education, and standard of living from various surveys listed in column 1 using the methodology described in *Technical note 5* at https://hdr.undp.org/sites/default/files/2025_HDR/hdr2025_technical_notes.pdf.

Column 4 and 5: Population data from UNDESA (2024b).

Columns 13 and 14: World Bank 2024b.

TABLE 7

Planetary pressures–adjusted Human Development Index

		Human Development Index (HDI)	Planetary pressures–adjusted HDI (PHDI)			Adjustment factor for planetary pressures	SDG 9.4 Carbon dioxide emissions per capita (production)	Carbon dioxide emissions (production) index	SDG 8.4, 12.2 Material footprint per capita	Material footprint index
		Value	Value	Difference from HDI value[a] (%)	Difference from HDI rank[a]	Value	(tonnes)	Value	(tonnes)	Value
HDI RANK		2023	2023	2023	2023	2023	2023	2023	2023	2023
Very high human development										
1	Iceland	0.972	0.735	24.4	-40	0.756	10.0	0.869	32.2	0.643
2	Norway	0.970	0.723	25.5	-49	0.746	7.1	0.907	37.5	0.584
2	Switzerland	0.970	0.732	24.5	-41	0.755	3.7	0.951	39.8	0.559
4	Denmark	0.962	0.792	17.7	-6	0.824	4.6	0.940	26.4	0.708
5	Germany	0.959	0.785	18.1	-9	0.819	7.2	0.907	24.3	0.730
5	Sweden	0.959	0.810	15.5	2	0.845	3.4	0.955	24.0	0.734
7	Australia	0.958	0.700	26.9	-59	0.731	14.5	0.811	31.5	0.651
8	Hong Kong, China (SAR)	0.955	..	..	..	..	4.5	0.941	..	..
8	Netherlands	0.955	0.740	22.5	-27	0.775	6.7	0.912	32.7	0.638
10	Belgium	0.951	0.666	30.0	-76	0.700	7.1	0.907	45.7	0.494
11	Ireland	0.949	0.752	20.8	-20	0.793	6.8	0.911	29.4	0.674
12	Finland	0.948	0.748	21.1	-22	0.789	5.7	0.926	31.4	0.652
13	Singapore	0.946	0.618	34.7	-90	0.653	8.2	0.893	53.0	0.412
13	United Kingdom	0.946	0.827	12.6	11	0.875	4.5	0.941	17.3	0.808
15	United Arab Emirates	0.940	0.585	37.8	-97	0.622	24.1	0.685	39.8	0.559
16	Canada	0.939	0.643	31.5	-79	0.684	14.2	0.815	40.3	0.554
17	Liechtenstein	0.938	..	..	..	..	4.0	0.948	..	..
17	New Zealand	0.938	0.731	22.1	-28	0.779	5.8	0.925	33.1	0.634
17	United States	0.938	0.686	26.9	-57	0.731	14.4	0.811	31.5	0.651
20	Korea (Republic of)	0.937	0.745	20.5	-16	0.795	11.2	0.854	23.9	0.736
21	Slovenia	0.931	0.791	15.0	7	0.850	5.3	0.930	20.8	0.769
22	Austria	0.930	0.757	18.6	-3	0.814	6.5	0.915	25.8	0.714
23	Japan	0.925	0.785	15.1	7	0.849	8.0	0.895	17.9	0.802
24	Malta	0.924	0.799	13.5	14	0.864	3.4	0.956	20.5	0.773
25	Luxembourg	0.922	0.479	48.0	-122	0.519	10.7	0.861	74.2	0.178
26	France	0.920	0.804	12.6	20	0.874	4.2	0.945	17.7	0.804
27	Israel	0.919	0.709	22.9	-34	0.772	6.5	0.915	33.6	0.628
28	Spain	0.918	0.818	10.9	24	0.891	4.7	0.939	14.2	0.843
29	Czechia	0.915	0.764	16.5	7	0.835	8.2	0.894	20.2	0.776
29	Italy	0.915	0.801	12.5	20	0.876	5.3	0.930	16.2	0.821
29	San Marino	0.915	..	..	..	..	..	..	..	..
32	Andorra	0.913	..	..	..	..	5.3	0.931	..	..
32	Cyprus	0.913	0.754	17.4	2	0.826	5.7	0.926	24.7	0.726
34	Greece	0.908	0.803	11.6	24	0.884	5.3	0.930	14.6	0.838
35	Poland	0.906	0.792	12.6	21	0.874	7.1	0.908	14.5	0.840
36	Estonia	0.905	0.714	21.1	-23	0.789	7.6	0.901	29.1	0.677
37	Saudi Arabia	0.900	0.666	26.0	-52	0.740	19.9	0.740	23.5	0.739
38	Bahrain	0.899	0.632	29.7	-63	0.703	24.6	0.679	24.6	0.728
39	Lithuania	0.895	0.751	16.1	4	0.840	4.6	0.940	23.6	0.739
40	Portugal	0.890	0.797	10.4	27	0.896	3.6	0.953	14.5	0.839
41	Croatia	0.889	0.787	11.5	24	0.886	4.4	0.943	15.5	0.828
41	Latvia	0.889	0.749	15.7	5	0.843	3.6	0.954	24.2	0.732
43	Qatar	0.886	0.276	68.8	-117	0.311	42.6	0.444	74.1	0.179
44	Slovakia	0.880	0.770	12.5	21	0.875	5.3	0.931	16.3	0.819
45	Chile	0.878	0.784	10.7	25	0.893	3.9	0.949	14.6	0.838
46	Hungary	0.870	0.757	13.0	19	0.870	4.0	0.948	18.8	0.792
47	Argentina	0.865	0.763	11.8	22	0.882	4.3	0.944	16.3	0.819
48	Montenegro	0.862	..	..	..	..	3.7	0.951	..	..
48	Uruguay	0.862	0.804	6.7	40	0.933	2.3	0.970	9.5	0.895
50	Oman	0.858	0.581	32.3	-69	0.677	16.9	0.779	38.5	0.574
51	Türkiye	0.853	0.729	14.5	1	0.854	5.0	0.934	20.4	0.774
52	Kuwait	0.852	0.531	37.7	-82	0.624	23.0	0.699	40.8	0.548
53	Antigua and Barbuda	0.851	..	..	..	..	6.8	0.911	..	..
54	Seychelles	0.848	..	..	..	..	5.1	0.933	..	..
55	Bulgaria	0.845	0.740	12.4	13	0.875	5.4	0.930	16.2	0.821
55	Romania	0.845	0.739	12.5	10	0.874	3.4	0.955	18.6	0.794
57	Georgia	0.844	0.772	8.5	32	0.915	3.2	0.959	11.6	0.871
58	Saint Kitts and Nevis	0.840	..	..	..	..	4.9	0.936	..	..
59	Panama	0.839	0.643	23.4	-43	0.766	3.1	0.959	38.5	0.573

Continued →

TABLE 7

		Human Development Index (HDI)	Planetary pressures–adjusted HDI (PHDI)			Adjustment factor for planetary pressures	SDG 9.4 Carbon dioxide emissions per capita (production)	Carbon dioxide emissions (production) index	SDG 8.4, 12.2 Material footprint per capita	Material footprint index
		Value	Value	Difference from HDI value[a] (%)	Difference from HDI rank[a]	Value	(tonnes)	Value	(tonnes)	Value
HDI RANK		2023	2023	2023	2023	2023	2023	2023	2023	2023
60	Brunei Darussalam	0.837	0.600	28.3	-55	0.717	26.0	0.661	20.4	0.774
60	Kazakhstan	0.837	0.687	17.9	-20	0.820	13.0	0.830	17.1	0.811
62	Costa Rica	0.833	0.774	7.1	37	0.929	1.6	0.979	11.0	0.878
62	Serbia	0.833	0.724	13.1	4	0.869	5.9	0.923	16.7	0.815
64	Russian Federation	0.832	0.710	14.7	-2	0.853	12.6	0.836	11.7	0.871
65	Belarus	0.824	..	..	..	..	5.9	0.922	..	..
66	Bahamas	0.820	0.712	13.2	0	0.868	6.1	0.921	16.7	0.815
67	Malaysia	0.819	0.677	17.3	-21	0.827	8.4	0.890	21.4	0.763
68	North Macedonia	0.815	0.754	7.5	32	0.925	3.6	0.953	9.3	0.897
69	Armenia	0.811	0.761	6.2	38	0.938	2.7	0.964	8.0	0.912
69	Barbados	0.811	..	..	..	..	4.2	0.945	..	..
71	Albania	0.810	0.755	6.8	35	0.933	1.8	0.976	10.0	0.889
72	Trinidad and Tobago	0.807	..	..	..	..	22.4	0.708	..	..
73	Mauritius	0.806	..	..	..	..	3.2	0.958	..	..
74	Bosnia and Herzegovina	0.804	0.701	12.8	-3	0.872	6.3	0.918	15.7	0.826
High human development										
75	Iran (Islamic Republic of)	0.799	0.725	9.3	14	0.907	9.2	0.880	5.9	0.934
76	Saint Vincent and the Grenadines	0.798	..	..	..	..	2.3	0.970	..	..
76	Thailand	0.798	0.726	9.0	18	0.910	3.7	0.952	11.9	0.869
78	China	0.797	0.644	19.2	-27	0.808	8.3	0.891	24.9	0.724
79	Peru	0.794	0.757	4.7	43	0.953	1.6	0.979	6.6	0.927
80	Grenada	0.791	..	..	..	..	2.7	0.965	..	..
81	Azerbaijan	0.789	0.737	6.6	27	0.934	4.2	0.945	6.9	0.924
81	Mexico	0.789	0.721	8.6	14	0.914	3.8	0.951	11.2	0.876
83	Colombia	0.788	0.740	6.1	34	0.939	2.0	0.974	8.6	0.905
84	Brazil	0.786	0.702	10.7	7	0.893	2.2	0.971	16.6	0.816
84	Palau	0.786	..	..	..	..	12.3	0.839	..	..
86	Moldova (Republic of)	0.785	0.738	6.0	32	0.940	1.7	0.977	8.8	0.903
87	Ukraine	0.779	0.717	8.0	18	0.920	3.7	0.952	10.0	0.889
88	Ecuador	0.777	0.735	5.4	32	0.946	2.4	0.969	6.9	0.923
89	Dominican Republic	0.776	0.726	6.4	28	0.936	2.8	0.963	8.3	0.908
89	Guyana	0.776	..	..	..	..	4.4	0.943	..	..
89	Sri Lanka	0.776	0.754	2.8	47	0.971	0.9	0.988	4.1	0.955
92	Tonga	0.769	..	..	..	..	1.8	0.976	..	..
93	Maldives	0.766	..	..	..	..	4.0	0.948	..	..
93	Viet Nam	0.766	0.699	8.7	9	0.913	3.4	0.956	11.7	0.870
95	Turkmenistan	0.764	0.667	12.7	-7	0.874	9.7	0.873	11.4	0.874
96	Algeria	0.763	0.706	7.5	18	0.926	3.9	0.949	8.8	0.902
97	Cuba	0.762	0.723	5.1	28	0.949	2.1	0.973	6.8	0.924
98	Dominica	0.761	..	..	..	..	2.2	0.971	..	..
99	Paraguay	0.756	0.689	8.9	9	0.912	1.2	0.985	14.6	0.839
100	Egypt	0.754	0.726	3.7	35	0.963	2.4	0.969	3.9	0.956
100	Jordan	0.754	0.714	5.3	26	0.947	1.9	0.976	7.4	0.918
102	Lebanon	0.752	0.691	8.1	13	0.919	3.6	0.953	10.3	0.886
103	Saint Lucia	0.748	..	..	..	..	2.8	0.963	..	..
104	Mongolia	0.747	0.577	22.8	-31	0.773	13.6	0.823	25.0	0.723
105	Tunisia	0.746	0.703	5.8	23	0.942	2.6	0.966	7.3	0.919
106	South Africa	0.741	0.685	7.6	11	0.924	6.7	0.913	5.8	0.936
107	Uzbekistan	0.740	0.702	5.1	24	0.949	3.5	0.954	5.1	0.944
108	Bolivia (Plurinational State of)	0.733	0.675	7.9	8	0.921	1.9	0.975	12.1	0.866
108	Gabon	0.733	0.704	4.0	27	0.961	2.2	0.971	4.4	0.951
108	Marshall Islands	0.733	..	..	..	..	3.7	0.952	..	..
111	Botswana	0.731	0.698	4.5	21	0.954	2.5	0.967	5.3	0.941
111	Fiji	0.731	..	..	..	..	1.2	0.984	..	..
113	Indonesia	0.728	0.684	6.0	15	0.940	2.6	0.966	7.7	0.915
114	Suriname	0.722	..	..	..	..	4.2	0.945	..	..
115	Belize	0.721	0.670	7.1	10	0.929	1.6	0.979	10.9	0.879
115	Libya	0.721	0.629	12.8	-7	0.872	8.9	0.884	12.7	0.859
117	Jamaica	0.720	0.686	4.7	21	0.953	2.7	0.965	5.2	0.942
117	Kyrgyzstan	0.720	0.699	2.9	27	0.971	1.5	0.980	3.4	0.962

Continued →

		Human Development Index (HDI)	Planetary pressures–adjusted HDI (PHDI)			Adjustment factor for planetary pressures	SDG 9.4 Carbon dioxide emissions per capita (production)	Carbon dioxide emissions (production) index	SDG 8.4, 12.2 Material footprint per capita	Material footprint index
		Value	Value	Difference from HDI value[a] (%)	Difference from HDI rank[a]	Value	(tonnes)	Value	(tonnes)	Value
HDI RANK		2023	2023	2023	2023	2023	2023	2023	2023	2023
117	Philippines	0.720	0.680	5.6	17	0.944	1.3	0.983	8.6	0.905
120	Morocco	0.710	0.679	4.4	19	0.956	1.8	0.976	5.8	0.935
121	Venezuela (Bolivarian Republic of)	0.709	0.652	8.0	7	0.920	3.5	0.955	10.4	0.885
122	Samoa	0.708	..	..	..	..	1.1	0.985	..	..
123	Nicaragua	0.706	0.668	5.4	16	0.946	0.8	0.990	8.8	0.902
124	Nauru	0.703	..	..	..	..	4.5	0.941	..	..
Medium human development										
125	Bhutan	0.698	0.593	15.0	-8	0.849	2.2	0.972	24.7	0.727
126	Eswatini (Kingdom of)	0.695	..	..	..	..	0.9	0.988	..	..
126	Iraq	0.695	0.665	4.3	13	0.957	3.9	0.949	3.2	0.964
128	Tajikistan	0.691	0.673	2.6	21	0.974	0.9	0.988	3.6	0.960
129	Tuvalu	0.689	..	..	..	..	1.0	0.987	..	..
130	Bangladesh	0.685	0.666	2.8	18	0.972	0.7	0.991	4.3	0.952
130	India	0.685	0.656	4.2	14	0.957	2.1	0.972	5.2	0.942
132	El Salvador	0.678	0.638	5.9	9	0.941	1.3	0.983	9.1	0.899
133	Equatorial Guinea	0.674	0.644	4.5	14	0.955	3.6	0.953	3.9	0.957
133	Palestine, State of	0.674	0.653	3.1	16	0.969	0.7	0.992	4.9	0.946
135	Cabo Verde	0.668	..	..	..	..	0.9	0.988	..	..
136	Namibia	0.665	0.611	8.1	5	0.918	1.6	0.979	12.8	0.858
137	Guatemala	0.662	0.626	5.4	9	0.946	1.1	0.985	8.5	0.906
138	Congo	0.649	0.631	2.8	12	0.973	1.3	0.984	3.5	0.962
139	Honduras	0.645	0.620	3.9	10	0.961	1.0	0.986	5.9	0.935
140	Kiribati	0.644	..	..	..	..	0.5	0.993	..	..
141	Sao Tome and Principe	0.637	..	..	..	..	0.7	0.991	..	..
142	Timor-Leste	0.634	..	..	..	..	0.5	0.994	..	..
143	Ghana	0.628	0.604	3.8	7	0.962	0.6	0.992	6.2	0.932
143	Kenya	0.628	0.610	2.9	8	0.971	0.4	0.995	4.8	0.946
145	Nepal	0.622	0.592	4.8	4	0.952	0.5	0.993	7.9	0.912
146	Vanuatu	0.621	..	..	..	..	0.7	0.991	..	..
147	Lao People's Democratic Republic	0.617	0.570	7.6	-3	0.923	3.2	0.958	10.0	0.889
148	Angola	0.616	0.604	1.9	11	0.980	0.6	0.993	2.9	0.967
149	Micronesia (Federated States of)	0.615	..	..	..	..	1.3	0.983	..	..
150	Myanmar	0.609	0.593	2.6	9	0.973	0.6	0.993	4.2	0.953
151	Cambodia	0.606	0.572	5.6	1	0.944	1.2	0.984	8.7	0.903
152	Comoros	0.603	..	..	..	..	0.5	0.993	..	..
153	Zimbabwe	0.598	0.585	2.2	8	0.978	0.7	0.991	3.1	0.965
154	Zambia	0.595	0.585	1.7	9	0.983	0.4	0.995	2.7	0.970
155	Cameroon	0.588	0.574	2.4	5	0.976	0.3	0.995	4.0	0.956
156	Solomon Islands	0.584	..	..	..	..	0.4	0.995	..	..
157	Côte d'Ivoire	0.582	0.537	7.7	-6	0.922	0.5	0.994	13.5	0.850
157	Uganda	0.582	0.569	2.2	3	0.978	0.1	0.998	3.9	0.957
159	Rwanda	0.578	0.567	1.9	4	0.980	0.1	0.999	3.4	0.962
160	Papua New Guinea	0.576	0.566	1.7	4	0.982	0.8	0.989	2.3	0.974
161	Togo	0.571	0.562	1.6	4	0.984	0.3	0.996	2.5	0.972
162	Syrian Arab Republic	0.564	0.553	2.0	4	0.981	1.1	0.986	2.2	0.976
163	Mauritania	0.563	0.542	3.7	2	0.962	0.9	0.988	5.8	0.936
164	Nigeria	0.560	0.548	2.1	5	0.979	0.6	0.993	3.2	0.965
165	Tanzania (United Republic of)	0.555	0.541	2.5	3	0.975	0.3	0.997	4.3	0.953
166	Haiti	0.554	0.545	1.6	6	0.984	0.3	0.996	2.5	0.972
167	Lesotho	0.550	..	..	..	..	1.7	0.978	..	..
Low human development										
168	Pakistan	0.544	0.529	2.8	2	0.973	0.8	0.989	3.9	0.956
169	Senegal	0.530	0.512	3.4	0	0.966	0.7	0.991	5.4	0.940
170	Gambia	0.524	0.514	1.9	2	0.982	0.3	0.997	3.0	0.966
171	Congo (Democratic Republic of the)	0.522	0.517	1.0	4	0.990	0.0	0.999	1.8	0.980
172	Malawi	0.517	0.507	1.9	2	0.980	0.1	0.999	3.5	0.961
173	Benin	0.515	0.504	2.1	1	0.978	0.4	0.995	3.5	0.961
174	Guinea-Bissau	0.514	..	..	..	..	0.1	0.998	..	..
175	Djibouti	0.513	0.480	6.4	-6	0.936	0.4	0.994	11.0	0.878
176	Sudan	0.511	0.498	2.5	2	0.974	0.4	0.995	4.2	0.954

Continued →

HDI RANK		Human Development Index (HDI)	Planetary pressures–adjusted HDI (PHDI)			Adjustment factor for planetary pressures	SDG 9.4 Carbon dioxide emissions per capita (production)	Carbon dioxide emissions (production) index	SDG 8.4, 12.2 Material footprint per capita	Material footprint index
		Value	Value	Difference from HDI value[a] (%)	Difference from HDI rank[a]	Value	(tonnes)	Value	(tonnes)	Value
		2023	2023	2023	2023	2023	2023	2023	2023	2023
177	Liberia	0.510	0.505	1.0	5	0.990	0.1	0.998	1.7	0.982
178	Eritrea	0.503	0.496	1.4	3	0.986	0.2	0.998	2.4	0.974
179	Guinea	0.500	0.488	2.4	2	0.975	0.3	0.996	4.1	0.955
180	Ethiopia	0.497	0.487	2.0	2	0.980	0.1	0.998	3.5	0.962
181	Afghanistan	0.496	0.492	0.8	5	0.991	0.3	0.997	1.2	0.986
182	Mozambique	0.493	0.486	1.4	3	0.986	0.2	0.997	2.3	0.975
183	Madagascar	0.487	0.481	1.2	3	0.988	0.1	0.998	2.0	0.977
184	Yemen	0.470	0.465	1.1	1	0.989	0.3	0.996	1.6	0.982
185	Sierra Leone	0.467	0.459	1.7	1	0.983	0.1	0.998	2.9	0.967
186	Burkina Faso	0.459	0.453	1.3	1	0.987	0.3	0.997	2.0	0.978
187	Burundi	0.439	0.435	0.9	1	0.991	0.1	0.999	1.6	0.982
188	Mali	0.419	0.411	1.9	1	0.981	0.3	0.996	3.2	0.965
188	Niger	0.419	0.410	2.1	0	0.979	0.1	0.999	3.6	0.960
190	Chad	0.416	0.397	4.6	0	0.954	0.2	0.998	8.1	0.910
191	Central African Republic	0.414	0.407	1.7	2	0.983	0.0	0.999	2.9	0.968
192	Somalia	0.404	0.396	2.0	1	0.979	0.0	1.000	3.7	0.959
193	South Sudan	0.388	0.383	1.3	1	0.986	0.1	0.998	2.3	0.974
Other countries or territories										
..	Korea (Democratic People's Rep. of)	..	..	..	..	0.961	2.3	0.970	4.2	0.953
..	Monaco	..	..	..	..	..	..	..	..	..
Human development groups										
	Very high human development	0.914	0.741	18.9	—	0.811	9.4	0.877	23.0	0.746
	High human development	0.777	0.677	12.9	—	0.871	5.6	0.926	16.6	0.816
	Medium human development	0.656	0.631	3.8	—	0.963	1.6	0.980	4.9	0.945
	Low human development	0.515	0.505	1.9	—	0.980	0.4	0.995	3.2	0.964
Developing countries		0.712	0.653	8.3	—	0.917	3.6	0.953	10.7	0.881
Regions										
	Arab States	0.719	0.665	7.5	—	0.926	4.6	0.940	8.1	0.911
	East Asia and the Pacific	0.775	0.658	15.1	—	0.849	6.5	0.916	19.7	0.782
	Europe and Central Asia	0.818	0.731	10.6	—	0.893	5.0	0.934	13.3	0.852
	Latin America and the Caribbean	0.783	0.715	8.7	—	0.913	2.7	0.965	12.5	0.861
	South Asia	0.672	0.644	4.2	—	0.959	2.1	0.973	5.0	0.945
	Sub-Saharan Africa	0.568	0.553	2.6	—	0.974	0.7	0.991	3.8	0.958
Least developed countries		0.560	0.548	2.1	—	0.978	0.3	0.996	3.6	0.960
Small island developing states		0.739	..	..	—	..	2.7	0.965	..	..
Organisation for Economic Co-operation and Development		0.916	0.752	17.9	—	0.821	8.2	0.893	22.6	0.750
World		**0.756**	**0.680**	**10.1**	**—**	**0.900**	**4.5**	**0.941**	**12.7**	**0.859**

Notes

a Based on countries for which a Planetary pressures-adjusted Human Development Index value is calculated.

Definitions

Human Development Index (HDI): A composite index measuring average achievement in three basic dimensions of human development—a long and healthy life, knowledge and a decent standard of living. See *Technical note 1* at 5 at https://hdr.undp.org/sites/default/files/2025_HDR/hdr2025_technical_notes.pdf for details on how the HDI is calculated.

Planetary pressures-adjusted HDI (PHDI): HDI value adjusted by the level of carbon dioxide emissions and material footprint per capita to account for the excessive human pressure on the planet. It should be seen as an incentive for transformation. See *Technical note 6* at 5 at https://hdr.undp.org/sites/default/files/2025_HDR/hdr2025_technical_notes.pdf for details on how the PHDI is calculated.

Difference from HDI value: Percentage difference between the PHDI value and the HDI value.

Difference from HDI rank: Difference in ranks on the PHDI and the HDI, calculated only for countries for which a PHDI value is calculated.

Adjustment factor for planetary pressures: Arithmetic average of the carbon dioxide emissions index and the material footprint index, both defined below. A high value implies less pressure on the planet.

Carbon dioxide emissions per capita (production): Carbon dioxide emissions produced as a consequence of human activities (use of coal, oil and gas for combustion and industrial processes, gas flaring and cement manufacture), divided by midyear population. Values are territorial emissions, meaning that emissions are attributed to the country in which they physically occur.

Carbon dioxide emissions (production) index: Carbon dioxide emissions per capita (production-based) expressed as an index using a minimum value of 0 and a maximum value of 76.61 tonnes per capita. A high value on this index implies less pressure on the planet.

Material footprint per capita: Material footprint is the attribution of global material extraction to a country's domestic final demand. Total material footprint is the sum of the material footprint for biomass, fossil fuels, metal ores and nonmetal ores. This indicator is calculated as the raw material equivalent of imports plus domestic extraction minus raw material equivalents of exports. Material footprint per capita describes the average material use for final demand.

Material footprint index: Material footprint per capita expressed as an index using a minimum value of 0 and a maximum value of 90.27 tonnes per capita. A high value on this index implies less pressure on the planet.

Main data sources

Column 1: HDRO calculations based on data from Barro and Lee (2018), IMF (2024), UNDESA (2024a), UNESCO Institute for Statistics (2024), United Nations Statistics Division (2025) and World Bank (2024a).

Column 2: Calculated as the product of the HDI and the adjustment factor presented in column 5.

Column 3: Calculated based on data in columns 1 and 2.

Column 4: Calculated based on PHDI ranks and recalculated HDI ranks for countries for which a PHDI value is calculated.

Column 5: Calculated based on data in columns 7 and 9.

Column 6: Global Carbon Project 2024.

Column 7: Calculated based on data in column 6.

Column 8: United Nations Environment Programme 2024.

Column 9: Calculated based on data in column 8.

Developing regions

Arab States (20 countries or territories)
Algeria, Bahrain, Djibouti, Egypt, Iraq, Jordan, Kuwait, Lebanon, Libya, Morocco, State of Palestine, Oman, Qatar, Saudi Arabia, Somalia, Sudan, Syrian Arab Republic, Tunisia, United Arab Emirates, Yemen

East Asia and the Pacific (26 countries)
Brunei Darussalam, Cambodia, China, Fiji, Indonesia, Kiribati, Democratic People's Republic of Korea, Lao People's Democratic Republic, Malaysia, Marshall Islands, Federated States of Micronesia, Mongolia, Myanmar, Nauru, Palau, Papua New Guinea, Philippines, Samoa, Singapore, Solomon Islands, Thailand, Timor-Leste, Tonga, Tuvalu, Vanuatu, Viet Nam

Europe and Central Asia (17 countries)
Albania, Armenia, Azerbaijan, Belarus, Bosnia and Herzegovina, Georgia, Kazakhstan, Kyrgyzstan, Republic of Moldova, Montenegro, North Macedonia, Serbia, Tajikistan, Türkiye, Turkmenistan, Ukraine, Uzbekistan

Latin America and the Caribbean (33 countries)
Antigua and Barbuda, Argentina, Bahamas, Barbados, Belize, Plurinational State of Bolivia, Brazil, Chile, Colombia, Costa Rica, Cuba, Dominica, Dominican Republic, Ecuador, El Salvador, Grenada, Guatemala, Guyana, Haiti, Honduras, Jamaica, Mexico, Nicaragua, Panama, Paraguay, Peru, Saint Kitts and Nevis, Saint Lucia, Saint Vincent and the Grenadines, Suriname, Trinidad and Tobago, Uruguay, Bolivarian Republic of Venezuela

South Asia (9 countries)
Afghanistan, Bangladesh, Bhutan, India, Islamic Republic of Iran, Maldives, Nepal, Pakistan, Sri Lanka

Sub-Saharan Africa (46 countries)
Angola, Benin, Botswana, Burkina Faso, Burundi, Cabo Verde, Cameroon, Central African Republic, Chad, Comoros, Congo, Democratic Republic of the Congo, Côte d'Ivoire, Equatorial Guinea, Eritrea, Kingdom of Eswatini, Ethiopia, Gabon, Gambia, Ghana, Guinea, Guinea-Bissau, Kenya, Lesotho, Liberia, Madagascar, Malawi, Mali, Mauritania, Mauritius, Mozambique, Namibia, Niger, Nigeria, Rwanda, Sao Tome and Principe, Senegal, Seychelles, Sierra Leone, South Africa, South Sudan, United Republic of Tanzania, Togo, Uganda, Zambia, Zimbabwe

Note: All countries listed in developing regions are included in aggregates for developing countries. Countries included in aggregates for Least Developed Countries and Small Island Developing States follow UN classifications, which are available at https://www.un.org/ohrlls/. Countries included in aggregates for Organisation for Economic Co-operation and Development are listed at http://www.oecd.org/about/membersandpartners/list-oecd-member-countries.htm.

Statistical references

Note: Statistical references relate to statistical material presented in this *Statistical Annex* and in the full set of statistical tables posted at https://hdr.undp.org/en/human-development-report-2025.

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