6

AI's Political Impact: Reshaping Power Within and Across Countries

Main messages

- AI is changing power dynamics between countries, corporations, and citizens, amplifying existing power imbalances and creating new ones.
- AI offers developing countries a real opportunity to transform their economies and societies, but geopolitical constraints, misaligned incentives, and intentional misuse of the technology may result in harm.
- Developing countries' access to AI infrastructure is dependent on geopolitics; however, pursuing "AI sovereignty" is expensive and not always effective.
- Generous incentives to attract AI investment may strain government resources, while the unanticipated use of state power and close ties between governments and AI firms could reduce the public benefits of such investment.
- Network effects and data feedback loops allow global AI companies to derive more value from user data than users themselves. AI also allows dominant firms—in the AI industry and beyond—as large employers to set terms in which wages are depressed, working conditions are diminished, and workers have limited ability to bargain.
- AI enables surveillance and the spread of propaganda in the absence of institutional checks and balances.

Introduction

In a quiet office in the capital of a developing country, Minister Maya faces a decision that will shape her country's technological future. Two proposals written by her advisers sit on her desk. One involves acquiring the latest artificial intelligence (AI) chips, the leading models, and cloud services from a small group of leading AI economies. The other involves her country building its own chips, models, and data centers. The first proposal enables her country to quickly acquire the capabilities of AI but risks her country becoming overly dependent on foreign providers.

The second proposal reduces dependence but may be prohibitively expensive. Choosing either proposal entails trade-offs.

A few miles away, Samuel, a resident of the capital city, walks past a new array of AI-powered cameras. At first, he welcomed them; they promised to reduce traffic congestion and speed up emergency response. But during a recent peaceful protest over rising living costs, the cameras were used to identify and track participants, turning a tool for public safety into an instrument of surveillance.

These scenes illustrate two of the four axes along which AI is changing power dynamics: between countries, between governments and corporations, between corporations and individuals, and between citizens and states. Although AI presents developing countries with an opportunity to transform their economies, power and politics will determine whether this opportunity is realized. The opportunity can be lost in three ways. Countries may *fail to access layers of the AI stack* because of geopolitics.[1] They may *waste the opportunity* because of misaligned incentives between governments and corporations, as well as between corporations and individuals. And governments may *misuse the opportunity* in their relationship with citizens.

What can go wrong along each axis depends on where power lies. Between countries, power stems from control over key inputs in the AI value chain: semiconductors, data centers, cloud networks, data, and critical minerals. Between corporations and governments, power arises from firms' control over frontier technologies and governments' authority over markets, regulation, and procurement. Between corporations and individuals, power reflects market structures that produce concentration, leaving users and workers with limited ability to push back on the terms companies set. Between states and citizens, power stems from the state's capacity to surveil, influence, and shape public discourse. Across all four axes, structural incentives can lead outcomes to diverge from the public interest.

AI does not determine political outcomes on its own. It expands the range of possibilities for surveillance as well as transparency, for manipulation as well as mobilization, and for concentration as well as diffusion of power. The outcomes depend on who controls the technology, who sets the rules for its use, and who has the capacity to contest those rules. Where institutions are weak and civic space is constrained, AI is more likely to amplify authoritarian tendencies; where the rule of law is robust and civil society is active, it can strengthen democratic accountability. This challenge places many developing countries in a difficult situation. They need AI to improve public services and accelerate economic growth but lack the resources to build domestic AI capacity and often have a weak regulatory environment to govern its use. This leaves them vulnerable to both state overreach and unfavorable terms of engagement with global technology firms, while limiting their influence over the rules being written.

This chapter examines how AI is reshaping these four axes of power, with particular attention to developing-country contexts. These four dimensions are neither exhaustive nor independent. They intersect and reinforce one another in ways that shape development outcomes. The chapter draws on evidence where such evidence exists and identifies gaps where the evidence is limited (or nonexistent).

Dynamics between countries: A technology with geopolitical stakes

States have long competed for control over transformative technologies. Naval power shaped imperial rivalry in the early modern period. Nuclear weapons and space technology became critical arenas of competition during the Cold War. Today, governments increasingly view AI as a foundational technology that shapes economic activity, social and political structures, national security, and global influence.[2] This dynamic will have significant repercussions for whether and how developing countries can access AI.

Since 2018, the United States has introduced export controls on advanced semiconductor chips and related supply chains, with exports to restricted entities requiring approval by the government.[3] Meanwhile, China has leveraged its control over critical raw materials by announcing a ban on the export of technologies to process rare earths, as well as export controls on the rare earth elements themselves.[4] China's latest measures also target technological know-how and foreign products made with Chinese inputs. However, several of the latest measures have been suspended until November 2026.[5]

Key layers of the AI stack can function as strategic "choke points": Control at each layer constrains who can participate in the AI value chain and acquire the capabilities of AI. Although open-source and open-weight models provide developing countries with access to models,[6] running models at scale requires either domestic data centers, which would have to be built on chips controlled by major powers, or commercial cloud providers based in some of these countries. Countries may seek to reduce dependence in several ways. One approach is to source different layers of the AI stack from different countries, choosing the best available technology for each layer. However, because AI systems depend on these layers working together, this strategy can create interoperability problems and expose countries to conflicting regulations tied to technologies from different jurisdictions. Pursuing "AI sovereignty" is an alternative approach, but as will be discussed, it is often a costly and ineffective one. Part 1 argued that AI offers developing countries an opportunity to ease shortfalls in skilled capabilities. Mishandling such trade-offs could cost developing economies access to this very technology.

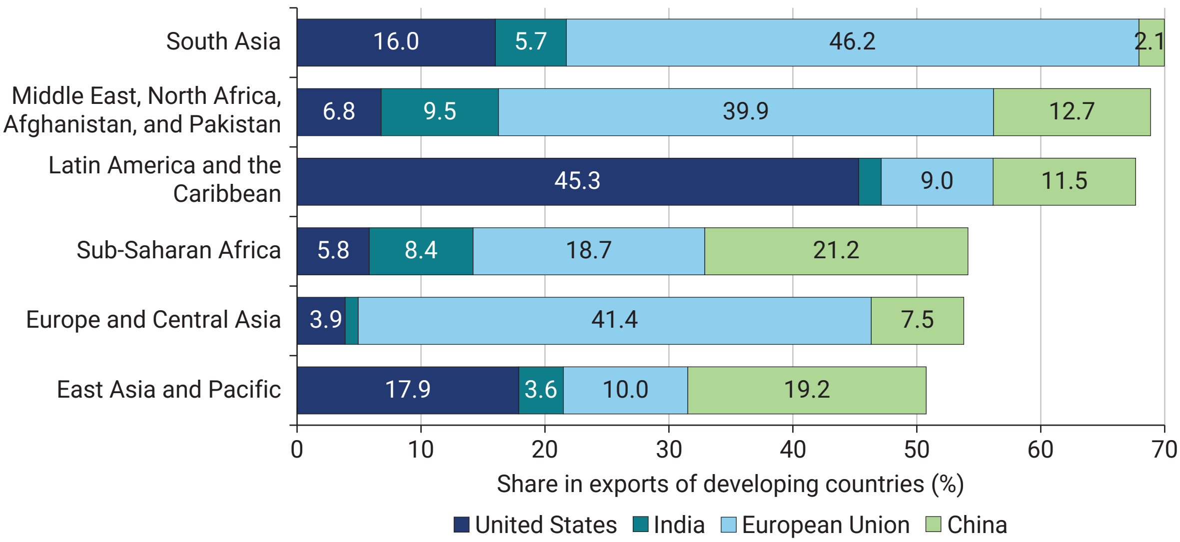
Incentives and asymmetric dependence shape technology choices

Why do the major powers promote the use of their AI technology? The first reason relates to scale. As discussed in part 1, AI benefits from economies of scale at many layers of the stack. The second reason involves influence. Having control over the AI infrastructure determines whose rules become the dominant global standard. More than 80 percent of the world's population lives in developing countries. Every additional country whose infrastructure, developers, and users are tied to a given technological ecosystem contributes to scale economies, strengthening the influence of the leading powers.

Notably, these powers often use incentives to promote their technology through financing and market access. The American AI Exports Program, launched under a US executive order in July 2025, promotes exporting US-developed "full-stack" AI technologies consisting of hardware, software, and services to allies to secure global technology leadership.[7] China's Digital Silk Road, launched in 2015 as part of the Belt and Road Initiative, aims to build crucial infrastructure in developing countries, including 5G networks, undersea cables, AI laboratories, data centers, and smart cities.[8]

Beyond incentives, asymmetric dependencies can also influence a country's technology choices. One common form of asymmetric dependency is that of trade.[9] Developing countries often rely heavily on a single major economy for trade (refer to figure 6.1). For example, developing countries in Latin America export a disproportionate share of their goods to the United States compared with other major powers, while those in East Asia and Pacific export an approximately equal share of goods to China and the United States—suggesting the presence of asymmetric dependencies with not just one but both countries.

Figure 6.1 Developing countries depend heavily on a few major economies as export destinations



Source: WDR 2026 team, based on data of the CEPII-BACI (Centre d'études prospectives et d'informations internationales/Center for Prospective Studies and International Information–Base pour l'Analyse du Commerce International/Database for International Trade Analysis) Dataset, CEPII, https://www.cepii.fr/DATA_DOWNLOAD/baci/doc/baci_webpage.html.

Note: The bars use 2024 data. *Developing countries* are defined as low-income, lower-middle-income, and upper-middle-income countries based on the World Bank fiscal year 2027 income classification. (Refer to Metreau et al. 2026; World Bank Country and Lending Groups [dashboard], World Bank, https://datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lending-groups.) China and India are excluded from the export share data even though they belong to the regions of East Asia and Pacific and South Asia, respectively. This is done to avoid mixing their role as both a source and a destination country. The United States and all European Union member countries are classified as high-income countries and are therefore also excluded from the export share data.

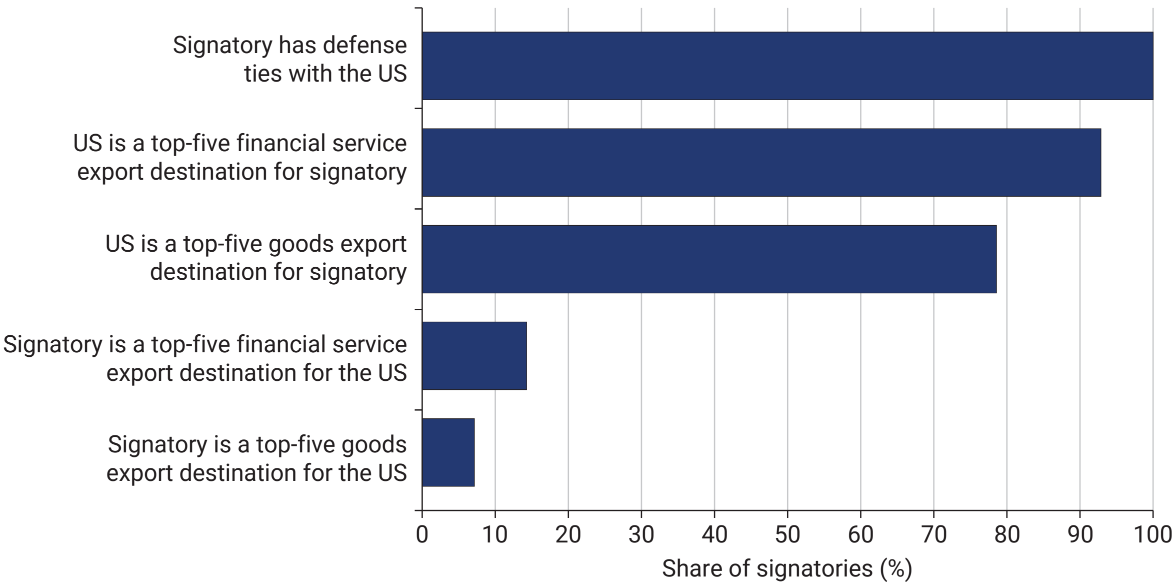
Trade dependencies, as well as dependencies in other domains such as security and financial systems, can reinforce one another. Crucially, the power arising from such imbalances need not be exercised or even articulated to be effective. Where one country is materially dependent on another across many domains, the mere existence of such asymmetric dependencies can shape the technology choices countries make.[10] The choices developing countries faced in the late 1990s regarding technologies related to genetic modification provide an instructive parallel. States with closer ties to the European Union were more likely to ratify the Cartagena Protocol on Biosafety early, whereas those closer to the United States were slower to support it or did not support it at all.[11]

In the case of AI, similar dynamics surrounding dependencies can be observed in the signing of the Pax Silica Declaration. Launched by the United States in 2025, the Pax Silica Initiative spans the entire AI stack and aims to reduce coercive dependencies, secure global technology supply chains, address AI supply chain opportunities and vulnerabilities, and explore joint investment, as well as protect sensitive technologies and build trusted digital infrastructure.[12] At the time of writing, signatories to the declaration include Australia, Finland, Greece, India, Israel, Japan, the Republic of Korea, Norway, the Philippines, Qatar, Singapore, Sweden, the United Arab Emirates, and the United Kingdom. These signatory countries tend to rely on the United States for defense and trade, even as the United States depends less on them as export destinations (refer to figure 6.2). Other strategic factors, such as the opportunity to be a partner in deploying capital and building infrastructure to accelerate national AI objectives, may also explain why some countries have chosen to participate. Although few of the participants are developing countries, the role that such dependencies may play in influencing their decisions makes it pertinent for developing economies.

Raw materials and data are rarely sufficient to rebalance the dependency that developing countries have on the major AI powers

A striking feature of the AI ecosystem is that, while control over the highest-value segments of the AI stack is concentrated in a few leading economies, several raw materials essential to this stack are geographically concentrated in developing economies (for further details, refer to chapter 2). In principle, control over these critical raw materials could give developing countries an opportunity to rebalance their interactions with leading economies. However, extraction alone

Figure 6.2 Pax Silica Declaration signatories share strong defense, economic, and trade ties with the United States



Source: WDR 2026 team, based on data of the CEPII-BACI (Centre d'études prospectives et d'informations internationales/ Center for Prospective Studies and International Information–Base pour l'Analyse du Commerce International/Database for International Trade Analysis) Dataset, CEPII, https://www.cepii.fr/DATA_DOWNLOAD/baci/doc/baci_webpage.html, and WTO-OECD (World Trade Organization-Organisation for Economic Co-operation and Development) Balanced Trade in Services dataset, https://www.wto.org/english/res_e/statis_e/gstdh_batis_e.htm

Note: A country is considered to have defense ties with the United States if it hosts or provides access to a US military base, has a framework agreement with the United States for defense cooperation, or has a defense pact with the United States. Financial service exports include the categories *financial services* and *insurance and pension services*. Goods export values are calculated by aggregating all products between each exporter-importer pair.

rarely translates into bargaining power without downstream processing capacity, which most developing countries lack. Discovered mineral reserves cannot always be extracted in a commercially viable way.

Data can be another potential counterbalancing force. Many developing countries generate large volumes of data that remain relatively untapped. For the major powers, access to such data is attractive for model development and market access alike. However, data in many developing countries are highly fragmented[13]—scattered across informal systems and government agencies and divided among dozens or hundreds of language communities, often too small individually to justify building specialized AI models.

The pursuit of AI sovereignty risks becoming a development trap

Faced with concerns about overdependence, many governments have started to adopt strategies to reduce dependence by securing ownership or control of the key physical resources that power AI. Although these strategies may also serve economic objectives, they are often framed as efforts to achieve AI sovereignty. Measures to achieve this include developing local models and capabilities to manufacture semiconductors, subsidizing domestic computing infrastructure,[14] and localizing data. From a national standpoint, AI sovereignty measures are rational if the objective is reduced dependence; they may also help countries move up the AI value chain. However, these measures often fail to deliver the promised sovereignty or a sustainable economic path for developing economies.[15]

First, AI sovereignty measures frequently fail to achieve their intended goals, especially if the goals involve complete self-sufficiency. Data localization can be complicated by the extraterritorial reach of a cloud provider's home-country laws, which may be triggered in situations such as serious criminal investigations.[16] Domestic semiconductor initiatives often struggle to match the scale economies of established incumbents. Even countries with a local data center may not be able to avoid upstream dependencies on hardware and software from major foreign providers.[17]

Second, AI sovereignty strategies commit governments to building at home, and this can generate domestic political costs. AI infrastructure is resource-intensive. As a result, AI sovereignty strategies bring to the forefront of political discourse concerns about the siting of such infrastructure, especially data centers.[18] In Malaysia, the state of Johor, which is the fastest-growing data center hub in Southeast Asia, is facing community backlash over the rapid expansion of data centers.[19] Similar opposition has emerged in other developing countries such as Brazil and Mexico.[20] Unlike a commercial developer that can relocate to another country if blocked in one, a government that has staked a sovereignty claim on building data centers cannot. It faces the political liabilities of public backlash as well as absorbing the fiscal cost of the abandoned or delayed project—often for an unmet goal.

Third, AI sovereignty imposes an aggregate cost through fragmentation. AI benefits from scale. Integrated global markets lower costs in many layers of the stack, such as those for training models, manufacturing chips, and building applications. Excessive fragmentation into duplicative country-level stacks reverses these scale economies. What emerges is a form of a self-reinforcing "fragmentation doom loop,"[21] which can create a development trap. Efforts to duplicate resources are already prohibitively expensive. Yet the more countries fragment, the more expensive it is for them to build their own AI stacks, adding strain to already-weak fiscal balances and diverting resources from pressing needs in health, education, or other infrastructure. Smaller developing countries bear a greater burden because they are unable to replicate at the national level the scale economies that they once accessed globally. By contrast, incumbent firms from the major powers continue to benefit by providing the AI stack and selling to the fragmented markets.

For developing countries, neither overdependence nor excessive fragmentation offers a sustainable path. Most countries cannot afford to build every layer from scratch. Thus, for most countries, the middle path between sovereignty and dependence is a more viable strategy. This entails, where possible, diversifying suppliers within each layer to reduce the risk of choke points while ensuring interoperability. It also involves targeted steps to reduce dependence, such as using open-source and open-weight models, establishing strong data governance, engaging in standards setting, and forming coalitions with like-minded countries to boost collective bargaining power. Part 3 of the Report builds upon such initiatives. This approach accepts that there will be trade-offs. Some choke points will persist, but this approach maintains access to economies of scale and frontier performance that outright sovereignty strategies would forgo.

Dynamics between governments and corporations: Entanglements could impede development

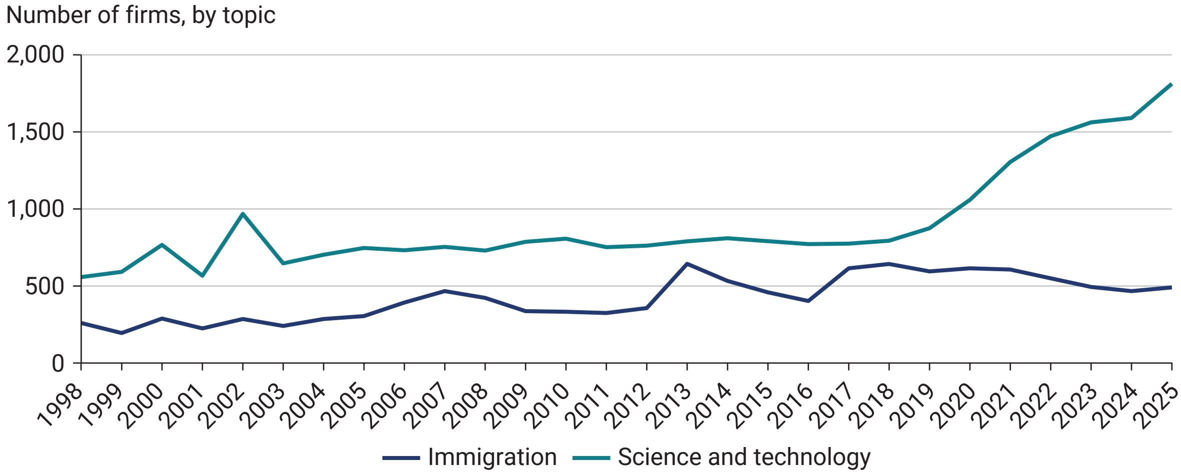
Within a country, the relationship between governments and corporations affects whether the gains from AI are broad based, wasted, or concentrated in the hands of existing power holders. Governments can lean too far toward accommodating firms, offering preferential terms to attract investment, at the expense of public funds. At times, governments may exercise their regulatory and enforcement powers in an unanticipated way, creating uncertainty for firms. In some instances, the relationship can settle into arrangements that are too cooperative, entrenching the interests of both through government-backed contracts flowing to connected firms and firms aiding in the extension of state power over citizens.

Each of these phenomena can be partly attributed to the same underlying cause of many imbalances of power between firms and governments. Firms lobby at scale.[22] The number of firms lobbying in the United States on AI-related issues nearly doubled between 2019 and 2025,[23] even as lobbying activity concerning issues such as immigration remained relatively constant during this period (refer to figure 6.3).[24] Active industry engagement in the European Union led to a shift in regulatory approach toward innovation and competitiveness.[25] An extensive investigation by the Centro Latinoamericano de Investigación Periodística and various partners documented nearly 3,000 lobbying actions across multiple economies between 2012 and 2025, with such activity rising rapidly in Latin America.[26]

Even without lobbying, these companies wield significant influence stemming from their position across the AI stack.[27] Moreover, because throughout the AI ecosystem switching costs are substantial, the possibility that a firm may reduce operations or withdraw owing to unfavorable regulations is credible, even without explicit threats. In some instances, because the technology is evolving so quickly, as government officials and agencies formulate policies and regulations, they may rely on the very corporations that they are tasked with regulating to explain the technology's abilities and potential risks.

Governments are not powerless. They retain significant levers such as export controls,[28] regulating access to domestic markets,[29] designations of supply chain risk,[30] and procurement rules (refer to chapter 8), as well as acquiring stakes in companies.[31] However, it is not easy to strike the right balance in using these levers. When used too readily, they can create uncertainty for firms, but when used too sparingly, governments may become too accommodative to firms or settle into arrangements that are too cooperative.

Figure 6.3 Since the launch of GPT-1 in 2018, the number of firms engaged in AI-related lobbying in the United States has rapidly increased



Source: WDR 2026 team, based on data of Top Issues (dashboard), OpenSecrets, https://www.opensecrets.org/federal-lobbying/top-issues.

Note: The year 2018 corresponds to the launch of the first OpenAI large language model, Generative Pre-trained Transformer 1 (GPT-1). The plotted lines show the total number of firms engaged in lobbying by issue. The AI-related category *science and technology* is the combined total of *science and technology, computers and information technology, and manufacturing*. Lobbying on *immigration* is shown separately. If a firm lobbies on more than one issue, it is counted multiple times in the data. AI = artificial intelligence.

In developing countries, the power imbalance between firms and governments is often exacerbated by weak state capacity. This implies that even for countries that navigate the geopolitics well and can secure access to various layers of the AI stack, the opportunities for AI to transform their economies can still be wasted because of the ways in which domestic governments engage with AI firms. Three outcomes are highlighted next. Each lets the opportunity slip away in different ways: straining government finances, foreclosing the investment that is needed, or channeling the gains to those who already hold power.

Competition to attract AI investment strains government finances and maneuver room

When firms are able to secure significant concessions from governments, competition among countries to attract AI-related investments may lead some countries to commit significant fiscal resources. Examples of fiscal commitments abound. In Uzbekistan, the government has introduced policies to attract investment in AI and data centers through tax exemptions and discounted electricity rates.[32] India has announced a 20-year tax holiday until 2047 for foreign providers of cloud services and data center operators.[33]

While these arrangements may incentivize AI investments, if entered into excessively, they may place a disproportionate share of the financial and technological risks on the public while allowing firms to capture a significant share of the economic returns. Fiscal balances in many developing countries are already deteriorating while pressure from rising debt is growing.[34] Such policies risk creating a race to the bottom in which countries undercut one another in offering incentives to attract investments, further straining fiscal space.

Fiscal commitments can also stimulate overinvestment in AI-related sectors, contributing to macroeconomic instability through boom-bust cycles. Episodes from history suggest that booms in technology are highly susceptible to such cycles, even in advanced economies (refer to box 6.1).

Unanticipated application of state power deters investment, while cozy arrangements between governments and firms could lead to rent seeking and weakened institutions

When firms cannot anticipate how state power will be applied, they factor this uncertainty into their choices by seeking higher returns, shortening investment commitments, or opting out entirely. Crucially, the fear is not regulation itself, given that firms routinely invest in heavily regulated environments, but rather sudden rule changes. The risk of unanticipated policy is compounded because much of the AI infrastructure, such as data centers and chip fabrication plants, requires large investments tied to specific locations. Once the investment is completed and the capital becomes sunk, the firm's ability to relocate declines. This shifts greater bargaining power to the host government, in a dynamic known as the "obsolescing bargain."[35] Governments can now raise preferential tax rates agreed upon before the investment was made, renegotiate access to land or power, introduce data localization requirements, and in extreme cases, expropriate the assets. Thus, reflecting the political risk, firms may make investments that have shorter commitments, limit transfers of capabilities, and create less local value.

Box 6.1 Boom, bang, bust in technology investments: Does history repeat itself?

Developments in artificial intelligence (AI) in the United States share certain characteristics with historical episodes like the railroads boom in the 1800s and the telecommunications boom of the late 1990s, in which the early promises of technological breakthroughs generated waves of exuberant expectations, massive leveraged investment, and eventual financial distress. Importantly, these episodes did not reflect technological failure but overinvestment based on overly optimistic forecasts. Although demand eventually caught up, the adjustment path was costly. Understanding how AI developments play out among firms in the United States matters because they are one of the dominant builders of the global AI infrastructure, including in developing countries. Whether a crash happens depends crucially on whether demand matches the high levels of investment.

High expectations of rapid growth. Past technology booms, like today's AI wave, have been marked by expectations of rapid growth in demand. A 1998 report by the US Department of Commerce claimed that internet traffic was doubling every 100 days—a figure later credited to WorldCom, a leading telecommunications company at the time.[a] This expectation underpinned a massive build-out of network infrastructure, even as growth rates slowed in subsequent years.[b] Similar expectations can be observed today and have been used to justify

(Box continues next page)

Box 6.1 Boom, bang, bust in technology investments: Does history repeat itself? *(continued)*

building ahead to meet anticipated demand. An analysis from 2018 shows that demand for compute has been doubling every 3.4 months[c]—a figure that is remarkably close to the 100-day doubling cited in the early days of the internet.

Elevated levels of capital investment. In anticipation of future demand, in past technology booms as well as the current AI wave, levels of capital investment have soared. The belief that the use of railroads and the internet would grow exponentially led to frenzied building of infrastructure. Between 1868 and 1871, rail companies in the United States built 33,000 miles of tracks, often in remote areas.[d] During the telecommunications boom, capital investment by publicly traded telecommunications service companies nearly tripled from $47 billion in 1995 to a peak of $121 billion in 2000.[e] The increase was so great that only 2.7 percent of fiber-optic lines were being used in 2002 when the sector crashed.[f] Strikingly, capital spending on AI by hyperscalers in the United States is expected to be about 2 percent of GDP in 2026, more than double the figure at the height of the telecommunications boom[g] and about the same as that on railroads in the 1860s.[h]

High level of debt. Elevated levels of capital investment that were mainly funded by debt have characterized past technology booms and the current AI wave. When financial crisis in Europe led to investors selling off railroad bonds in the 1870s, the market was flooded with more bonds than buyers were willing to absorb.[i] Telecommunications firms had run up total debts of about $1 trillion at the time of the crash.[j] Twenty-three telecommunications companies went bankrupt in a wave capped off by the collapse of WorldCom in 2002, the single largest bankruptcy in the history of the United States at that time.[k] Today, concerns are growing that AI hyperscalers are taking on excessive debt, as seen in their increasing share in the public investment-grade bond index and the increasingly complex structures of deals between AI companies.[l]

Source: WDR 2026 team.

a. *Economist* (2002b).
b. Couper et al. (2003).
c. OpenAI (2018). *Compute* is defined in this article as petaflop/s-days. A petaflop/s-day consists of performing 10^{15} neural net operations per second for one day, or a total of about 10^{20} operations.
d. Wooldridge (2025).
e. Doms (2004).
f. Dreazen (2002).
g. Slok et al. (2026).
h. Wooldridge (2025).
i. Refer to "Financial Panic of 1873" (web page), US Department of the Treasury, https://home.treasury.gov/about/history/freedmans-bank-building/financial-panic-of-1873.
j. *Economist* (2002a).
k. Starr (2002).
l. Sam et al. (2026).

Besides holding the power to change rules suddenly, governments control access to a range of valuable resources. Past experience suggests these resources can be allocated in ways that reflect political favoritism rather than competitive allocation.[36] As a result, capital, labor, and public funds can be directed toward firms that are politically connected rather than those that create the greatest economic value, weakening institutions in the process.[37]

A recent example is Indonesia's Pusat Data Nasional Sementara (Temporary National Data Center) project. Investigators found that a small group of opportunistic officials misused their contracting power to rig the tender process to benefit Lintasarta, a subsidiary of Indosat Ooredoo Hutchison group, in exchange for kickbacks. As a result, the state lost an estimated 140.8 billion rupiah.[38] Checks and balances held, however, and the officials were held accountable. The example provides a cautionary tale; if checks and balances fail and transparency is lacking, such conduct may evolve into systemic rent-seeking dynamics. Research from several countries has shown that politically connected firms tend to survive, yet industries with a higher share of such firms exhibit lower growth and productivity.[39] Over time, such misallocation reduces market dynamism, crowding out firms that would have generated more value. This process could diminish the broad-based gains AI could have generated and could concentrate the greatest gains in the hands of those who already hold power.

Beyond resource allocation, there is also the risk of firms being drawn into the exercise of state power. Many technology companies collect large volumes of personal information; governments increasingly request access to such data.[40] Although there may be legitimate security or law enforcement reasons for such requests and companies have safeguards in place, the rising frequency of these requests normalizes this access mechanism—which may be exploited to further the state's power over its citizens. Ultimately, the safeguards rely on mutual restraint—with companies pushing back on overreach and governments using such access judiciously. This equilibrium can easily go either way when there is a change in corporate policy or government.

Although the three outcomes discussed are distinct, they all stem in part from the imbalance of power between corporations (which supply the technology) and states (which depend on these technologies but are responsible for regulating them). Reducing or eliminating this imbalance is crucial to ensuring that countries do not let the opportunities for AI to deliver positive outcomes for their economies slip away. Part 3 of this Report discusses policies to avoid such outcomes.

Dynamics between corporations and individuals: Market structure determines who gains from AI

Unlike competition between states or contested bargains between governments and firms, the power imbalances between firms and individuals in the AI economy emerge from features of the AI value chain itself, such as large up-front investments, network effects, data feedback loops, and spillover effects that standard market mechanisms cannot address.[41] These characteristics lead to market concentration that benefits capital owners more than users and workers. Treating this concentration as a well-understood market failure rather than an inherent characteristic of the AI value chain helps clarify which policy tools can address it.

Data advantages lead to durable market power that benefits AI capital owners more than users

AI systems improve with use. Each user interaction generates data that can be used to train better models; better models attract more users; more users generate more data. This feedback loop makes it harder for new entrants to catch up once a leader has emerged. Moreover, users may find it costly to switch between providers. It is difficult for a business that has built workflows around one AI provider to move to another or for individuals to move their data and history between platforms. Other markets, such as those for operating systems and search engines, are characterized by similar tendencies for data advantages that compound concentration.

Data concentration is harder to address through standard competition tools than concentration in other inputs because of data externalities; that is, a single user's data are nearly redundant for predicting that user's own behavior, but useful for predicting the behavior of similar users.[42] This pattern has significant policy implications. Giving individuals property rights over their own data does little to prevent the concentration of AI's predictive capability. Even if many users withheld their data, firms holding the largest existing data sets would retain their advantage. Data externalities of this kind require collective governance arrangements rather than specific provisions of individual contracts between AI providers and users alone.

Beyond data concentration, individuals in many developing countries face significant challenges in understanding what happens to their data because minimal safeguards are in place. As of 2026, only 73 percent of developing countries have enacted data protection legislation, compared with 98 percent of advanced economies.[43] Even where such laws exist, they are rarely enforced. This concern has become increasingly important because data collected for one purpose are often repurposed to train models for entirely different applications, making it difficult to trace where the training data come from. Furthermore, documentation regarding the origin of training data, whether user consent was obtained, and the authenticity of the data remains insufficient.[44]

Several policy approaches are emerging to address these market failures. India's digital public infrastructure, built before the current AI wave, shows how public alternatives can prevent the concentration that AI is likely to intensify. The Unified Payments Interface is a government-provided payment system accounting for about 70 percent of India's digital payment volume as of fiscal year 2023–24. It processed more than 12 billion transactions in the single month of December 2023.[45] The interface is open and works with many systems, allowing any private company to build on it. This feature prevents the platform lock-in that often happens with payment systems in other countries. Meanwhile, India's Data Empowerment and Protection Architecture expands this model by giving individuals control over their data through consent managers and by enabling data portability.[46] While implementation challenges remain, the model has attracted interest from several countries.

Data cooperatives offer an alternative approach in which individuals pool their data to gain collective bargaining power that they lack individually, aggregating decisions that individual users cannot make effectively on their own and thus addressing the externality problem. Small-scale pilots in India and Kenya are testing this approach for gig workers and others in the informal sector, though evidence on their effectiveness at scale is limited.

These asymmetries are not new to AI; they characterize the platform economy more broadly, in which users generate the data that firms convert into commercial advantage. What AI changes is their intensity. When user interactions train the models that are a firm's main asset, data become more valuable to capture, one user's data reveal more about others, and switching providers gets harder. Individuals are left with limited means to bargain over how their data are used or to share in the returns they generate. Whether digital public infrastructure, open-weight models, data cooperatives, and competition policy enforcement can achieve sufficient coordination to shift these structural dynamics will depend on whether countries adopt and enforce the required policies and on effective international coordination that does not yet exist.

AI can concentrate power in the hands of capital owners at the expense of workers

The development of AI systems has created new employment opportunities for millions of relatively low-skill workers in developing countries—from data labeling for AI training to content moderation. These opportunities share a common feature that economists recognize as a source of market failure: A few large companies are the main source of jobs for many workers in the AI industry, giving these employers extra power over determining pay and working conditions. This phenomenon is what economists call a *monopsony*. Meanwhile, workers are being managed by algorithms; human managers are absent, for the most part. This type of algorithmic management at scale, combined with the monopsony powers of employers, results in AI companies paying wages below workers' additional contribution to total value,[47] working conditions that workers have little ability to negotiate, and a structural difficulty in workers organizing collectively.

The data labeling industry is a clear example. A few companies, such as Scale AI, Sama, CloudFactory, and Appen, hire workers from a large global pool of workers. High global labor supply combined with concentrated buyer-side demand drives down wages. A 2023 investigation in Kenya found that some data labelers earned between $1.32 and $2.00 per hour, barely above Kenya's minimum wage of about $1.20 per hour, for psychologically and emotionally challenging work that included reviewing graphic content.[48] In addition to low wages, workers must contend with sudden shutdowns of the platform, late or withheld payments, restrictions on workers organizing, and contracts designed to place legal liability in jurisdictions that favor the platforms. Fairwork Cloudwork Ratings, which evaluates platforms on five areas of fair work, found that none of the 16 platforms reviewed met basic standards of fair pay, working conditions, contracts, management, or worker representation.

The same AI systems that require labeled data to operate also depend on humans to filter out the most disturbing content. Content moderators and data workers who screen for disturbing content carry psychological costs that are well documented. A 2023 lawsuit by Kenyan content moderators against Meta and Sama found diagnoses of posttraumatic stress disorder (PTSD), depression, and anxiety among workers exposed to traumatic content without proper psychological support.[49] Much of this work is outsourced to developing countries,[50] where workers typically lack access to mental health services and other protections that are necessary for such disturbing work. This situation poses a difficult labor market problem: In a competitive market with sufficient information and bargaining power, workers taking on such risks would receive higher wages and structured psychological support. The combination of monopsony, a large global labor supply, and outsourcing through jurisdictions with weak labor protections has prevented those conditions from emerging. They persist, at least in part, because AI companies can shift the offshore locations for this work across countries at a relatively low cost.

Beyond the firms that are involved in the value chain of AI, businesses across the economy can potentially deploy AI to exercise greater control over workers. Algorithmic management is not inherently worse than human management; in some respects it can be fairer because consistent rules applied uniformly are easier to scrutinize than the discretionary and sometimes arbitrary decisions of a human supervisor.[51] The concern is not the algorithm itself but the conditions under which it operates: Workers cannot observe how decisions are made, have limited means to contest those decisions, and often face a single buyer with little ability to switch employers.

Under these conditions, the consistency that could make algorithmic management fairer instead entrenches the firm's advantage. Machine learning systems can monitor worker performance, tracking outputs, time allocation, and patterns as workers complete tasks extremely closely. Firms have always had advantages over workers in terms of information, but AI greatly reduces the cost of acting on those advantages at scale.[52]

This dynamic is most apparent in platform companies in which algorithms can make automated decisions about task assignment, pricing, and account status with limited human oversight. They can also deactivate workers' accounts, with limited options for appeal. Dynamic pricing that modifies prices constantly depending on supply and demand and other conditions shifts income variability from the platform onto the worker. Platform communication structures are often one-sided: Firms can reach individual workers directly, but workers cannot easily communicate with one another through the platform, making it harder to organize collectively. Box 6.2 highlights how these mechanisms play out in ride-hailing platforms and how courts and regulators have begun to respond in high-income countries.

In developing countries, most existing employment is in the informal sector. In Sub-Saharan Africa, informal employment accounts for 85 percent of total employment.[53] When algorithmic management enters informal sectors in these countries through apps for taxi drivers, delivery workers, or domestic workers, among others, it formalizes some aspects of work without bringing the protections traditionally associated with formalization, such as employment contracts, social security, and grievance mechanisms.

Box 6.2 How AI amplifies the market power of ride-hailing and delivery platforms

Ride-hailing platforms have become the most litigated case of algorithmic labor management. Uber uses artificial intelligence (AI) algorithms to manage approximately 9 million drivers worldwide, controlling every aspect of the job, including who gets which rides, how much the fare is, and whether a driver's account remains active. The platform modifies prices constantly by using machine learning algorithms to forecast demand. Drivers have no information about how these decisions are made, how the drivers themselves are rated, or why they are offered particular rides at specific prices. Each driver only sees their own transactions, but the platform tracks every transaction for every driver.

This information advantage translates into leverage for the platform. Drivers have no control over the algorithms. Drivers must maintain scores above a certain threshold to avoid deactivation under Uber's rating system. The platform continuously tracks acceptance and cancelation rates, response times, driving habits, and location. Algorithms adjust fares in real time. Performance categories determine which drivers get priority access to trips, creating what a Dutch court described as "a financial incentive and a disciplining and instructing effect."[a]

(Box continues next page)

Box 6.2 How AI amplifies the market power of ride-hailing and delivery platforms *(continued)*

Several countries have pushed back. In 2021, the United Kingdom Supreme Court declared that Uber drivers are "workers" entitled to minimum wage and paid leave. That same year, a Dutch court ruled that algorithmic management constituted a "modern relationship of authority" and deemed Uber an employer. Spain's Rider Law compels delivery platforms to treat couriers as employees and establishes worker rights regarding algorithmic management and labor protections.

Platforms have responded in three ways. Some exit markets when confronted with employment classification, as Deliveroo did in Spain following the passage of the Rider Law in 2021. Others switch to subcontracting models that preserve algorithmic control while avoiding direct employment. A third group lobbies for intermediate legal categories that retain flexibility without granting full employment rights. Proposition 22 in California is the most prominent example.

What distinguishes this dynamic from conventional employment disputes is AI's ability to scale and automate control. Algorithms can monitor thousands of workers simultaneously, adjust pricing across entire cities in seconds, and enforce performance standards with no human oversight. This shifts the balance of power in ways that individual workers cannot counter. A driver cannot negotiate with an algorithm, appeal to its discretion, or organize fellow drivers when the platform controls who sees which messages. Although AI is not the only source of monopsony power,[b] it makes exercising the powers held by employers cheaper, faster, and harder to contest.

Source: WDR 2026 team.

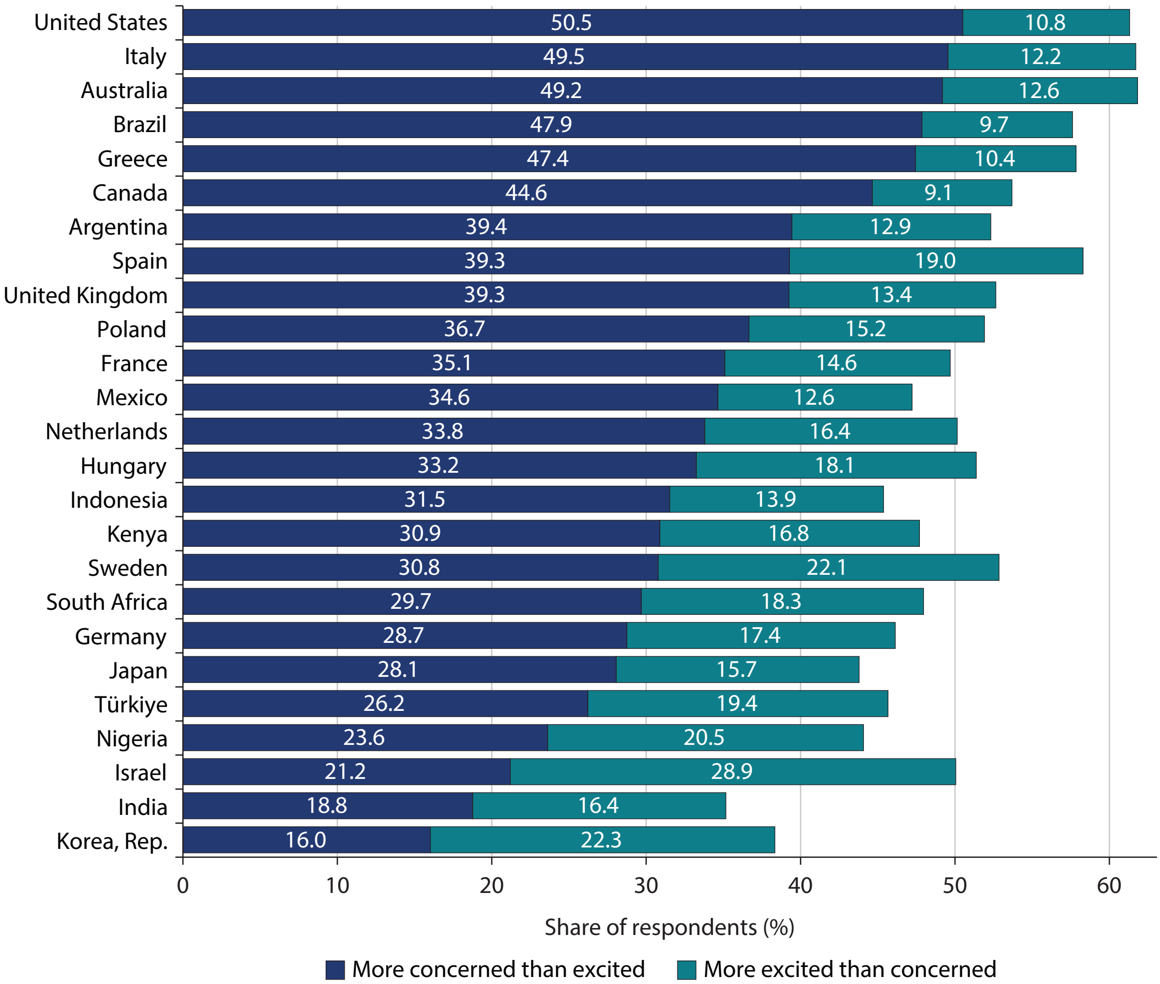
a. Refer to ruling from Court of Amsterdam, 8937120 CV EXPL 20-22882, September 13, 2021, https://www.courthousenews.com/wp-content/uploads/2021/09/amsterdam-uber-ruling.pdf.

b. *Monopsony* refers to a market in which there is a single buyer or a small group of dominant buyers: in the context of this box, employer.

Dynamics between citizens and the state: AI strengthens the state's hand, for better or worse

AI is changing the relationship between states and their citizens in two opposing directions. While AI can improve the delivery of public services (refer to chapter 5), it can also facilitate widespread surveillance, polarize public discourse, and sway voter behavior. Public perceptions of AI in developing countries reflect this dichotomy. Among surveyed low- and middle-income countries, levels of concern are highest in Brazil and Argentina (and similar to those in the United States and Europe), and lowest in Nigeria and India (refer to figure 6.4). These differences show that attitudes concerning AI are influenced by the context of the country, not only its income level.

Figure 6.4 Attitudes toward AI vary widely across countries



Sources: Poushter et al. 2025. Data for the United States are from the American Trends Panel Wave 152, Pew Research Center, https://www.pewresearch.org/dataset/american-trends-panel-wave-152/.

Note: The data are from the Global Attitudes Survey, Spring 2025 edition, Pew Research Center (Poushter et al. 2025). For each country, the bars show only the "more concerned than excited" and "more excited than concerned" responses and hence do not total 100 percent. The remaining share comprises respondents who did not answer or responded with "equally concerned and excited." AI = artificial intelligence.

AI makes surveillance cheap and scalable

Surveillance by government is not new. What AI changes is its scale, precision, and cost. Facial recognition can identify individuals in crowds in real time. Predictive analytics can flag potential targets before they act. Natural language processing can scan millions of messages for keywords or sentiment. These capabilities can transform surveillance from a targeted activity requiring significant resources into a persistent, scalable one.

Autocracies and weak democracies are more likely to import surveillance technologies, such as facial recognition AI, especially following episodes or periods of domestic political unrest; the technologies, once deployed, in turn suppress subsequent unrest.[54] The scope of AI surveillance extends beyond physical monitoring to include analysis of online behavior, social networks, and communication patterns. At least 75 countries were using AI surveillance technologies as of 2019, and adoption was increasing in all regions, the Carnegie Endowment's AI Global Surveillance Index reports.[55] This figure is likely a lower bound given the improvements in performance of recent AI models.

Many low- and middle-income countries have weak rule of law, limited checks on executive power, and constrained civic space. In such contexts, AI surveillance technologies can shift the balance between the state and citizens. In the absence of robust data protection laws, independent judiciaries, and effective oversight mechanisms, misuses of AI face few institutional constraints.

The use of AI for surveillance or predictive policing can also result in mistargeting and disproportionate enforcement among marginalized groups due to preexisting biases in policing data that get encoded in AI algorithms.[56] This problem extends to judicial decision-making, in which algorithmic tools used to inform bail, sentencing, and parole decisions can reproduce racial and socioeconomic disparities.[57] These problems may be compounded in developing countries, where training data are scarcer and populations may be more diverse. The underlying issue is that supervised learning methods reproduce the patterns present in their training data, including discriminatory ones.

Another concern is that AI surveillance could constrain civic space even without formal repression as people change their behavior because they know they are being monitored (so-called chilling effects). The extent to which this dynamic operates in low- and middle-income countries is an empirical question that warrants further research.

AI surveillance systems also raise concerns about due process. Unlike traditional surveillance, which typically requires warrants and documentation, AI systems can flag individuals automatically and trigger investigations without human review. The opacity of these systems means that individuals may be unable to contest their classification, even when it is based on flawed data.

An additional concern is that technologies deployed for legitimate governance objectives can be repurposed for surveillance. During the COVID-19 pandemic, Israel repurposed phone-tracking technology originally developed to combat terrorism for contact tracing to identify, notify, and monitor individuals who may have been exposed to the virus, prompting legal challenges.[58] Developing countries often lack the institutional checks, such as independent courts, privacy regulators, and active civil society, needed to prevent such function creep. The global diffusion of surveillance capabilities raises questions about the responsibility of the countries and firms that export these technologies.[59] Without international norms governing the export of surveillance technologies, these tools will continue to reach governments with weak accountability mechanisms.

AI can also enable citizen oversight of government. In Ukraine, for instance, the nongovernmental organization Transparency International Ukraine runs DOZORRO, which applies machine learning to the government's e-procurement system and ProZorro, the public electronic procurement system, to flag irregularities and routes citizen and civil society complaints to regulators and law enforcement bodies.[60] Since 2017, the project has reviewed thousands of risky tenders and has helped save Ukraine billions of dollars in public funds.[61] Whether AI strengthens accountability or surveillance depends on the institutional context and the distribution of technical capacity between the state and civil society.

Synthetic content erodes shared facts

Generative AI has substantially reduced the cost of producing convincing synthetic content like fake images, videos, and text. At least 16 countries had used generative AI to influence public debate, and at least 47 governments had deployed commentators to manipulate online discussions, as of 2023;[62] the number has probably grown since then. Deepfake videos of political candidates have appeared in many recent elections in many countries.[63] The implications for public deliberation are significant given that social media has increasingly become the primary source of information on current events[64] and individuals are largely incapable of distinguishing between AI- and human-generated text.[65]

AI-generated disinformation can erode the shared foundations of information necessary for democratic deliberation and undermine trust in electoral processes. These challenges are amplified in developing countries for several reasons. Media and information literacy tends to be lower. Fact-checking infrastructure remains limited: As of 2025, Africa had 66 active fact-checking organizations serving 1.5 billion people, compared with 139 in Europe serving 750 million.[66] Electoral management bodies often lack the technical capacity and resources to detect AI-enabled disinformation at scale.

The proliferation of synthetic content also makes it possible to dismiss authentic evidence as fabricated,[67] threatening accountability mechanisms that are central to governance quality.[68] When citizens cannot trust evidence of official misconduct, demanding explanations becomes futile and accountability breaks down.

AI systems can also analyze behavioral data to identify persuadable voters and deliver tailored messages. Large language models can test thousands of message variants and optimize for engagement in real time. Recent research finds that large language models can be highly persuasive using factual arguments, even when those arguments include misinformation.[69]

AI also creates possibilities for improving the integrity of information. Platforms using natural language processing allow citizens to report corruption or failures of public service delivery in local languages. AI-powered analysis of government budgets can help civil society organizations track public spending. Whether these applications can keep pace with the manipulative uses of the same technologies remains to be seen.

AI polarizes public discourse

Beyond direct manipulation, AI is also reshaping public discourse. Social media platforms use AI to personalize content and target ads. These AI algorithms analyze user behavior to predict what content will maximize engagement, creating feedback loops that reinforce emotional content over informational content. Research demonstrates that moral and emotional language in social media content increases the spread of these media through online networks; outrage is particularly contagious online.[70] This is the mechanism through which AI contributes to polarization: By systematically prioritizing content that triggers strong emotional reactions, algorithmic curation amplifies divisive messages while suppressing more measured discourse.

Internal research from Meta, disclosed in the Facebook Papers, showed that its engagement-maximizing algorithms have disproportionately promoted divisive content because such content has generated more engagement.[71] While this research focused on high-income countries, the dynamics operate globally. For example, in Myanmar, Facebook's algorithms helped amplify hate speech against Rohingya Muslims, contributing to what United Nations investigators described as potential genocide.[72] In Ethiopia, platform algorithms have been implicated in spreading inflammatory content during ethnic conflicts.[73]

Although the causal relationship between exposure to algorithmically curated content and changes in political attitudes or behavior is not fully established, algorithmic curation appears to exacerbate existing polarization in societies with weak institutions, limited media literacy, and deep ethnic or religious cleavages. Even if platforms do not create these divisions, they can intensify them by making emotionally charged content more visible than content encouraging compromise or mutual understanding.

Algorithmic curation is not the only way AI shapes public discourse. As citizens, journalists, civil servants, and analysts increasingly draft, summarize, and reason with the same chatbots—most of them trained abroad—the range of positions people express may narrow toward whatever those models treat as default. Controlled experiments show that exposure to opinionated language models can shift users' own expressed views,[74] that groups writing with a shared model produce less diverse text,[75] and that the same flattening appears in creative output.[76] These are short-term effects measured in experiments; whether they aggregate into societywide homogenization is not established. But the possibility matters most where pluralism, rather than consensus, is what holds a fragile political settlement together. In such settings, homogenization is a risk distinct from disinformation, and addressing it points toward supporting a plurality of models so that no single foreign-trained system becomes the default voice in a national public sphere.

These challenges are especially salient in lower-income countries because platforms have made limited investments in content moderation. For instance, Meta provides content moderation for only a fraction of the world's 7,000 languages.[77] When AI systems trained predominantly on high-resource languages make decisions about content in more regional or local languages like Amharic, Burmese, or Swahili, the error rates are predictably higher and result in both underdetection of hate speech and overflagging of legitimate discourse.

Polarization limits citizens' willingness to process information that contradicts their group identity.[78] Consequently, in contexts with significant societal divisions, algorithmically amplified polarization can make cooperation across groups even more difficult; weaken institutional accountability; and erode trust in government, media, and expertise. However, recent evidence suggests that low-cost interventions can reduce susceptibility to misinformation. In South Africa, biweekly fact-checks delivered via WhatsApp over six months improved citizens' ability to identify new misinformation, particularly when they received financial incentives to review those fact-checks.[79] In Mexico, simply providing voters with accurate information about local government performance during the COVID-19 pandemic backfired: Providing voters with unfavorable information about relative COVID-19 cases and deaths increased the vote share of incumbent candidates.[80] A short antipolarization message delivered alongside the same information reversed the backlash, restoring the link between performance and electoral accountability.

If governments can identify which citizens are susceptible to which messages, they can target disinformation and curtail it instead of disseminating it. Conversely, governments can use concerns about disinformation to justify expanded surveillance. This interaction means that the individual dynamics described earlier may compound in contexts in which institutional checks on both surveillance and information manipulation are weak. But even when governments are well intentioned, cybersecurity risks may pose challenges to their efforts, which can perpetuate mistrust in AI.

The evidence reviewed in this section suggests that deliberate policy choices—such as fact-checking, algorithmic transparency, and opportunities for citizens to deliberate—can counter the default trajectory. The investments required are not prohibitive. The main challenge may be the lack of institutional capacity and political will.

Policy choices will shape power imbalances among governments, corporations, and individuals

Power has always been about access and control, whether to land, capital, markets, or information. What distinguishes AI is the speed and scale at which it can redistribute access, often in ways invisible to those most affected. The governance challenge may be more fundamental than simply writing better rules or investing more resources. It may require rethinking what sovereignty means when essential infrastructure is privately owned and globally distributed, what accountability means when decisions are made by systems too complex for even their designers to fully explain, and what consent means when the costs of refusing to participate are too high for most people to bear.

A broader consideration is whether the current patterns shaping AI align with the needs of most of the world's population. Most people live in developing countries, work in informal sectors, speak languages other than English, and interact with institutions limited by capacity constraints. Yet AI systems are predominantly designed by and for populations in high-income countries—a relatively small fraction of humanity.

History shows that outcomes depend on choices about regulation, public investment, labor protections, and international cooperation. For developing countries, the path forward involves building governance capacity, making strategic investments in areas of comparative advantage, and coordinating with other countries to shape international norms. The technology does not determine outcomes; governance choices do.

Notes

1. The *AI stack*, as discussed in chapter 2, consists of five interdependent layers: applications, AI models, data, infrastructure, and hardware.
2. Allen and Chan (2017).
3. Sutter (2025).
4. Baskaran (2024); Szczepański (2025).
5. Szczepański (2025).
6. *Open-source models* provide transparency and customization, allowing those that build AI applications to access the model weights, architecture, training data, and source code, with minimal licensing restrictions. Examples include AI Singapore's Southeast Asian Languages in One Network (SEA-LION), Allen Institute for AI's Olmo models, BigScience Large Open-science Open-Access Multilingual (BLOOM) Language Model, EleutherAI's GPT-NeoX, Google's Bidirectional Encoder Representations from Transformers (BERT) models, and the Swiss AI Initiative's Apertus. *Open-weight models* allow developers to access the model weights, but restrict access to other areas. Examples include Chile's National Center for Artificial Intelligence's Latam-GPT, DeepSeek's models, Google's Gemma models, Lelapa AI's InkubaLM, and Meta's Llama models (although they are sometimes marketed as open source). A couple of OpenAI's GPT models also fall into this category.
7. United States, White House (2025).
8. As of 2019, China had reportedly spent $79 billion on projects related to the Digital Silk Road and, by 2020, had signed cooperation agreements or provided related investments to at least 16 countries (Kurlantzick 2020). The actual numbers are likely to be higher because many of these agreements are unreported.
9. Liu and Yang (2025).
10. Clayton et al. (2025).
11. Schneider and Urpelainen (2013).
12. Refer to Pax Silica (dashboard), Under Secretary for Economic Affairs, US Department of State, https://www.state.gov/pax-silica.
13. Kaushik et al. (2025); Marivate (2026).
14. *Computing infrastructure* refers to the hardware needed to train and run AI models, including specialized chips, networking and storage

equipment, along with the cooling and power systems that support them. Such infrastructure is often housed in data centers and can be accessed through cloud providers.

15. *AI sovereignty* is an ambiguous concept, with definitions ranging from the most ambitious form of complete self-sufficiency to more calibrated approaches involving control over certain parts of the AI value chain. Anthony (2025); Pava et al. (2026); Tanner et al. (2026).
16. Daskal (2018); Schwartz (2018). In part to address concerns surrounding data localization, cloud providers now offer various approaches with different degrees of sovereignty. Such approaches range from software-based controls, to clouds operated by domestic entities using the hyperscalers' technologies, to standalone environments deployed on premises or within secure facilities. For more information, refer to Meinhardt et al. (2026).
17. Narratives around AI sovereignty are often driven by foreign technological companies that operate under the laws of their own countries and benefit greatly from the demand that sovereignty generates. NVIDIA has been among its most visible proponents. Jensen Huang, NVIDIA's chief executive officer, declared that "every country needs sovereign AI" (Yew et al. 2025). Leading hyperscalers have developed specialized sovereign cloud solutions. For example, Amazon Web Services now provides the European Sovereign Cloud offering.
18. Regardless of whether it is built for economic or sovereign reasons, a data center tends to generate domestic political costs wherever it is built. The clearest illustration is in the United States, where the build-out has not been to reduce foreign dependence. Nonetheless, the building of data centers has mobilized considerable opposition across political lines and in many types of communities. In 2025, at least 48 data center projects, worth more than $156 billion, were blocked or delayed amid local opposition (DePillis 2026, citing research by Data Center Watch). Commonly cited concerns include rising utility bills, noise, and strain on grid capacity. In some cases, opposition has led to county- or statewide moratoriums, as well as suspensions of tax incentives. This pattern is not unique to the United States. Because of intense local opposition, Meta's planned 166-hectare data center in the Netherlands was halted in 2022, and so was Google's planned $1.1 billion data center in Luxembourg (Roach and Krukowska 2022). Media coverage in 2026 indicates that planning for Google's data center in Luxembourg is advancing despite opposition (Monaghan 2026).
19. Anand and Mookerjee (2026).
20. Mozur et al. (2025); Pooler (2026).
21. Clayton et al. (2025).
22. For example, refer to Bertrand et al. (2014); Blanes i Vidal et al. (2012); Blanga-Gubbay et al. (2025); Kang (2016).
23. 2025 data of Issue Profile: Science and Technology (dashboard), OpenSecrets, https://www.opensecrets.org/federal-lobbying/issues/summary?cycle=2025&id=SCI.
24. Despite the dramatic rise, only about 4 percent to 5 percent of firms participating in lobbying were lobbying on AI-related issues.
25. Csernatoni (2025); Jones (2023); Mukherjee and Chee (2025).
26. Agência Pública and CLIP (2025).
27. Narechania and Sitaraman (2024).
28. Since 2018, the United States has imposed a number of export controls on advanced semiconductor chips and the associated supply chain. The measures have compelled AI companies based in the United States, such as Advanced Micro Devices (AMD) and NVIDIA, to halt or modify sales to major Chinese customers, illustrating how state authority can override market incentives in strategically important sectors (Sutter 2025).
29. For example, in 2021, the Nigerian government indefinitely suspended Twitter's operations in response to disputes concerning content moderation and political expression (Oluorunbi 2021). The ban persisted for seven months and was lifted only when the company largely agreed to the government's demands (BBC 2022).
30. A notable example is the disagreements between Anthropic and the US government in 2026 over the company's refusal to relax AI safety guardrails for military use, specifically on autonomous weapons and mass surveillance. As a result, Anthropic was classified as a supply chain risk (Shalal et al. 2026).
31. For instance, in 2025, the US government agreed to purchase 433.3 million primary shares of Intel common stock at a discounted price of $20.47 per share, equivalent to a 9.9 percent stake in the company (Intel Corporation 2025). In recent years, state-owned entities in China have acquired golden shares in subsidiaries of major Chinese firms, such as Alibaba, ByteDance, and Tencent.
32. Reuters (2025).
33. Phartiyal (2026).
34. World Bank (2026).
35. Kobrin (1984); Vernon (1971).
36. Artunç and Saleh (2025); Faccio (2006); Fisman (2001).
37. *Rent seeking* refers to the practice of manipulating public policy or economic conditions as a strategy to increase profits.
38. *Jakarta Post* (2026).
39. Akcigit et al. (2023).
40. Refer to Government Requests for User Data (graphic), Meta, https://transparency.meta.com/reports/government-data-requests/.
41. *Network effects* refer to a phenomenon in which the value of a product or service increases exponentially as more people use it. As the user base grows, the service becomes more useful, secure, or valuable, creating a self-reinforcing loop that drives widespread adoption. *Data feedback loops*

refer to cyclical processes in which the output of a system is captured as data and fed back into the system as input to automatically trigger modifications, optimizations, or learning.
42. Kasy (2025).
43. UNCTAD (2026).
44. Longpre et al. (2024).
45. India, PIB (2024); Product Statistics: UPI (data page), National Payments Corporation of India, https://www.npci.org.in/product/upi/product-statistics.
46. India, NITI Aayog (2020).
47. Azar and Marinescu (2024); Dube et al. (2020).
48. Perrigo (2023).
49. Espada (2023).
50. Roberts (2019).
51. Ludwig and Mullainathan (2021).
52. Jarrahi et al. (2021); Kellogg et al. (2020).
53. ILO (2018).
54. Beraja et al. (2023).
55. Based on the latest available reliable information from Feldstein (2019).
56. Dressel and Farid (2018); Lee et al. (2024); Richardson et al. (2019).
57. Arnold et al. (2021); Dobbie et al. (2018).
58. Shwartz Altshuler and Hershkowitz (2020).
59. Hill (2021).
60. For details, refer to Nestulia et al. (2019).
61. Kelman and Yukins (2022).
62. Funk et al. (2023).
63. Bond (2024).
64. UNESCO (2025).
65. Kreps et al. (2022).
66. Ryan (2025).
67. Chesney and Citron (2019).
68. Larreguy et al. (2020); Pande (2011).
69. Hackenburg et al. (2025).
70. Brady et al. (2020).
71. Merrill and Oremus (2021).
72. UNHRC (2018).
73. BBC (2021); Hale and Peralta (2021).
74. Jakesch et al. (2023).
75. Anderson et al. (2024); Padmakumar and He (2024).
76. Doshi and Hauser (2024).
77. Merrill and Oremus (2021).
78. Larreguy and Raffler (2025).
79. Bowles et al. (2025).
80. Enríquez et al. (2025).

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