UNEC Journal of Computer Science and Digital Technologies
Volume 2, № 1, 2026, pp. 109-118
https://doi.org/10.30546/UNECCSDT.2026.001.271

Section:
Digital Transformation and
Emerging Technologies

The AI Divide: How Automation Deepens Digital Inequality

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Abstract

AI has worked its way into the machinery of everyday decisions, who is granted credit, which diagnosis a patient is given, whether a public service can be reached at all. Its benefits are not shared evenly. If anything, the distance between the countries that build these systems and those that only use them keeps widening rather than closing. This paper treats that distance as the AI Divide and reads it as a structural condition, not a passing lag. Five mechanisms feed it, and each one feeds the next: uneven access to infrastructure; labour disruption that lands hardest on developing economies; algorithmic bias that carries old discrimination into new tools; computing power gathered into a few hands; and an environmental cost paid largely by those who caused least of it. The evidence comes from a structured review of peer-reviewed work between 2016 and 2026, set against data from international institutions, and the numbers are not subtle. Adoption in richer economies runs about three-quarters higher than in poorer ones. Some 92 million jobs are expected to go by 2030, most of them where the means to retrain people are thinnest. Facial-recognition error climbs toward 35 percent for darker-skinned women while staying under 1 percent for lighter-skinned men. Three firms hold close to two-thirds of the world's clouds. Because no strand moves on its own, the divide tends to widen itself unless policy intervenes. The paper closes with five governance principles, universal access, data sovereignty, representative development, algorithmic accountability, and international cooperation, and asks what each would mean for Azerbaijan and the South Caucasus, where the problem is already here rather than hypothetical.

Keywords: Artificial Intelligence, Digital Inequality, Algorithmic Bias, AI Governance, South Caucasus

Received:	*Revised:*	*Accepted:*	*Published:*
20/05/2026	*03/06/2026*	*06/06/2026*	*17/06/2026*

1. Introduction

Artificial intelligence (AI) has left the laboratory. Only a few years ago it was a research subject; now it helps settle who gets a mortgage, tells a court which defendants to treat as high-risk, and steers where policing falls heaviest. Its commercial footprint has grown to match. Valued at roughly 538 billion US dollars in 2023, the global AI market is expanding at a compound annual growth rate of about 19 percent [1]. In the United States, private AI investment reached 67.2 billion US dollars that same year, around 8.7 times China's figure, and by 2024 the tools had passed a billion users [2]. Most of those users, though, are in developing countries that do not yet have the governance, infrastructure, or institutions to handle the risks that travel with them [3].

What makes AI different from earlier technological waves is a feedback loop baked into the way it works. Data sharpens the models; sharper models pull in more users, and those users' hand back still more data, which sets the cycle off again. Electricity and the internet spread unevenly too, but in the end, they reached most of the world. AI may not, and the reason is that the loop pays most for whoever is already ahead. A country with less data trains weaker tools, gets less back from them, and slips a little further behind on each turn of the wheel. Kanni Wignaraja of the United Nations put it plainly in late 2025: AI is racing ahead while many countries are still at the starting line [3].

For Azerbaijan the question is practical, not theoretical. The country has already built real digital infrastructure, through the ASAN (Azerbaijan Service and Assessment Network) platform and a string of e-government strategies, and that work settled a basic point: deliberate public investment in services pays off. It now faces a harder choice, namely, how to fold AI into those services before the rules governing them exist. So, the AI Divide is a governance problem in the present tense, not a forecast. The rest of the paper maps its five connected dimensions and locates Azerbaijan's exposure on each; from there it builds five governance principles on the same evidence.

2. Methodology and Analytical Framework

For a long time, work on digital inequality fixed on connectivity, on who can get online and who cannot [4]. With AI that framing is too narrow. The divide cuts through several layers of the technical and social system at once, and five mechanisms drive it. Access to infrastructure is uneven to begin with. That first gap shapes the next: labour disruption gathers in the Global South, while algorithmic bias works its way into decisions that carry real stakes. A fourth mechanism is concentration, since AI capability and the data feeding it have pooled in a handful of countries. The last is environmental, a burden shared unevenly. Table 1 lays out this framework and, for each mechanism, sets down where Azerbaijan stands.

Table 1. *Five-dimensional AI Divide framework with Azerbaijan exposure assessment.*

Dimension	Core mechanism	Global evidence	Azerbaijan exposure
Access	Infrastructure gap; 10.6 pp North-South adoption differential (H2 2025)	24.7% North vs. 14.1% South; 2.6 billion people offline; Africa holds 1% of data-centre capacity	About 18% adoption (middle tier); Azerbaijani underrepresented in AI training corpora
Labour	92 million jobs displaced by 2030 (WEF); up to 40% of jobs exposed (IMF)	170 million new roles, mainly in the Global North; structural geographic mismatch	Outsourcing, administration, and manufacturing at high risk; limited reskilling provision
Bias	Automated systems reproduce and amplify structural inequalities	About 35:1 facial-recognition error disparity; roughly double COMPAS false-positive rate for Black defendants	No AI audit mechanism; governance gap in ASAN public services
Geopolitics	Three US firms control about 65% of global cloud; data colonialism dynamics	US private AI investment 8.7 times China's; concentration of foundational models	Near-total reliance on foreign AI platforms; limited regulatory capacity
Environment	Data-centre demand 415 TWh (2024) rising	AI carbon footprint of 32.6 to 79.7 Mt CO_2	Climate-exposed South Caucasus; contributes

	toward 945 TWh (2030); asymmetric cost burden	by 2025; costs fall on low-capacity regions	negligibly yet bears disproportionate costs

Source: author's framework, drawing on [2], [3], [5], [6], [7]. CO_2 = carbon dioxide; COMPAS = Correctional Offender Management Profiling for Alternative Sanctions; pp = percentage points.

The review followed PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) principles, short of a full meta-analysis. Searches ran across Scopus and Web of Science for peer-reviewed work from 2016 to 2026, combining terms like "AI inequality," "digital divide," "algorithmic bias," "AI governance," and "automation displacement" with "developing countries" or "Global South." A study earned its place only when it was empirical or policy-analytical, appeared in English in a peer-reviewed venue, and bore on at least one of the five dimensions; opinion pieces, editorials, and high-income-only work with no comparative angle dropped out. The opening pass returned 412 records. After duplicates were removed and the rest screened, 136 remained; these shaped the synthesis below, with the most representative and recent among them cited directly. Those studies were read alongside institutional datasets, from the United Nations Development Programme (UNDP), the World Economic Forum (WEF), the International Energy Agency (IEA), the International Labor Organization (ILO) and the International Monetary Fund (IMF) to Stanford University's Human-Centered AI institute (HAI) and Oxford Insights. None of the five mechanisms, in the end, sits in a box of its own. Being shut out of access leaves a workforce more exposed to automation, and the same concentration of computing power that hardens algorithmic bias also pushes environmental costs onto the communities least able to carry them. Figure 1 follows that chain.

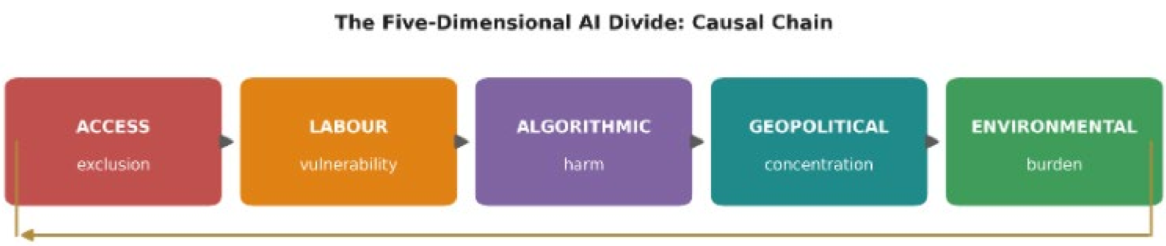

Figure 1. The five-dimensional AI Divide as a causal chain. Each dimension compounds the next, and the loop reinforces itself in the absence of deliberate policy intervention. Source: author.

3. Results and Discussion

3.1 Access and infrastructure

By the second half of 2025, the split was plain. Working-age adoption averaged 24.7 percent across the Global North and 14.1 percent across the Global South, a gap of 10.6 percentage points, up from 9.8 only six months earlier [8]. The infrastructure behind that gap is just as lopsided. Africa holds about 1 percent of global data-centre capacity, and cloud adoption there sits near 15 percent against 72 percent in Europe [9]. Table 2 gives country-level figures, and Figure 2 shows the distribution.

Table 2. *Global AI adoption rates by country, H1 to H2 2025 (%). Azerbaijan (estimate) is shown as a structural middle tier.*

Country / region	H1 2025 (%)	H2 2025 (%)	Status
UAE	n/a	64.0	Global North leader
Singapore	n/a	60.9	Global North leader

Norway	n/a	45.3	Global North
Global North average	22.9	24.7	Widening gap
Azerbaijan (estimate)	~16	~18	Middle tier
Global South average	13.1	14.1	Widening gap
Pakistan	n/a	9.6	Global South
Ethiopia	n/a	7.3	Global South, low
Malawi	n/a	4.2	Global South, low

Source: Microsoft AI Economy Institute [8]; Oxford Insights [10]; Stanford HAI [2].

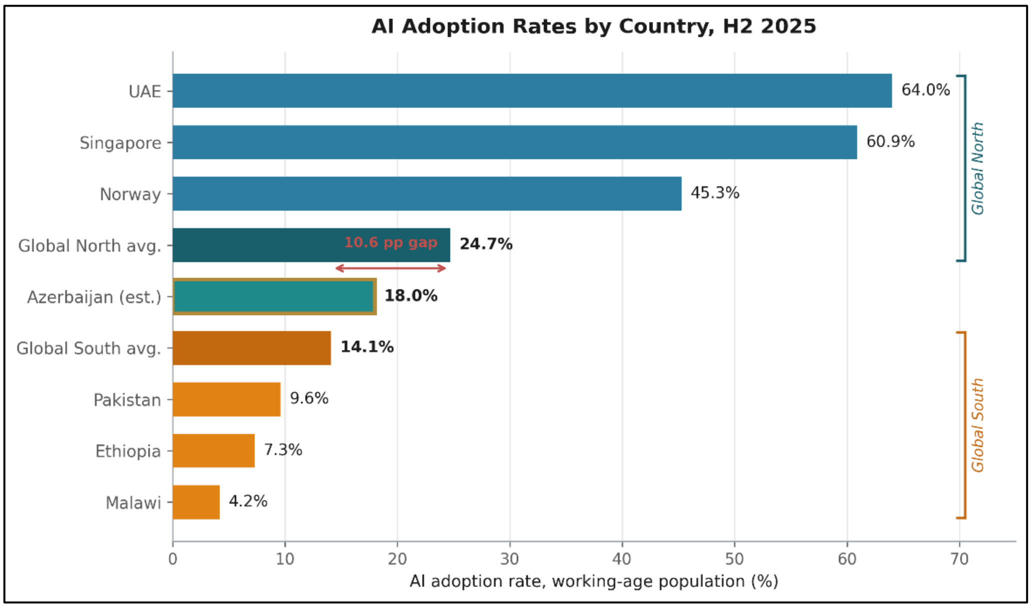

Figure 2. AI adoption rates by country, H2 2025. Azerbaijan (estimate) sits in the structural middle tier; the 10.6 pp North-South gap widened from 9.8 pp in six months, which indicates an accelerating rather than static divide. Source: [8], [10].

That leaves Azerbaijan in an uncomfortable middle: ahead of most of sub-Saharan Africa, far behind the front-runners, and not standing still. One handicap is worth pulling out. Azerbaijani barely appears in the text corpora that train large models, so tools built mainly on other languages simply work less well for the people who speak it. Worse, each new system trained on the same thin data carries the penalty forward [11].

3.2 Labour-market disruption

The WEF projects 92 million jobs displaced by 2030, set against 170 million created [5]. The IMF, looking at the same horizon, reckons generative AI could touch 40 percent of jobs worldwide [12]. The net figure flatters the picture. The roles that vanish are mostly in developing economies. The ones that appear in cluster where the infrastructure to absorb them is already in place [13]. Table 3 sets out displacement risk by sector with its relevance to the South Caucasus.

Table 3. *Sector-level AI displacement risk with South Caucasus relevance.*

Sector	Risk level	AI mechanism	Azerbaijan / South Caucasus relevance
Data entry / clerical	85%, very high	Document processing; RPA	Large clerical workforce; limited digital upskilling infrastructure

Customer service / BPO	78%, high	Conversational AI; automated resolution	Outsourcing sector growing; a major employment pathway at risk
Light manufacturing	62%, high	Robotics; automated quality control	Key export sector for transition economies; strategic vulnerability
Legal / paralegal	45%, moderate	Large language models for document review	Growing professional-services sector; risk emerging
Healthcare support	28%, lower	Diagnostic AI augments; human oversight retained	Augmentation more likely than acute structural disruption

Source: McKinsey Global Institute [14]; ILO [15]; WEF [5]. BPO = business process outsourcing; RPA = robotic process automation.

Azerbaijan's exposure is concentrated, and the list is short: business-process outsourcing (BPO), routine administration, labour-intensive manufacturing. All three are sectors with thin reskilling provision. The scale of the response required is sobering. Research from the OECD puts the cost of retraining workers in high-automation-risk jobs somewhere between 1 and 4.5 percent of gross domestic product (GDP). Actual public spending on training, averaged across OECD countries, sits at about 0.1 percent [16]. The distance between those two figures is the whole problem. The Digital Trade Hub initiative is a useful start, but at the current pace it will not build reskilling capacity before the displacement arrives. Comparable economies make the stakes clear: the ILO estimates that 26 to 38 percent of jobs in Latin America and the Caribbean are exposed to generative AI [15], and the South Caucasus profile is structurally similar. Working methodologies for assessing such risks at the level of individual firms are beginning to appear in the regional literature [17].

3.3 Algorithmic bias and discrimination

In the Gender Shades study, facial-recognition error rates climbed to roughly 35 percent for darker-skinned women while staying below 1 percent for lighter-skinned men, a gap of about 35 to 1 [18]. The Correctional Offender Management Profiling for Alternative Sanctions (COMPAS) recidivism tool, used in several US jurisdictions, flagged Black defendants with false positives at around twice the rate of white defendants [19]. A widely used healthcare algorithm turned out to understate the needs of Black patients in a consistent, patterned way [20]. None of this comes down to a stray bug in the code. It is what tends to happen when systems are built by similar-looking teams on training data that does not represent the people the system will end up judging, a pattern long documented in the fairness literature [21], [22] and in the technical bias surveys that followed [23], [24], [25].

Azerbaijan currently has no mechanism for auditing AI systems. As automated decisions enter public services through ASAN, a citizen harmed by a biased decision has no clear route to challenge it [26]. The European Union (EU) AI Act, adopted in 2024, offers a ready template: conformity assessments for high-risk systems, independent audit rights, and a genuine right of redress [27]. Azerbaijan need not design a framework from nothing; it needs the political will to adopt one.

3.4 Geopolitical concentration and environmental burden

Three US corporations, Amazon, Microsoft, and Google, run about 65 percent of the world's cloud infrastructure [28]. For a smaller state that is a sovereignty problem as much as an economic one: the systems that increasingly shape government decisions, credit scoring, and hiring belong to firms that answer no authority in Baku [29]. The environmental side is just as lopsided. The world's data centres drew roughly 415 terawatt-hours (TWh) of electricity in 2024, and the IEA expects that figure to climb toward 945 TWh by 2030, close to Japan's entire current demand [6]. By 2025, the carbon attached to all of this may sit somewhere between 32.6 and 79.7 million tonnes [7]. The South Caucasus, meanwhile, is one of the regions most exposed to drought, heat, and food insecurity, even though it adds almost nothing to those emissions. Table 4 maps the resulting governance gap across the five dimensions.

Table 4. *AI governance gap: Azerbaijan against global benchmarks across all five dimensions.*

Dimension	Global benchmark	Azerbaijan current status	Priority action
Access	Universal broadband and AI-infrastructure mandates	About 18% adoption; ASAN operational	Extend ASAN to AI-powered public services (P1)
Labour	Reskilling investment scaled to automation risk (OECD)	Digital Trade Hub underway; scale insufficient	Accelerate outsourcing and manufacturing reskilling (P3)
Bias	Mandatory algorithmic impact assessments (EU AI Act)	No AI audit; no bias testing in public services	Enact an algorithmic accountability law; audit ASAN (P4)
Geopolitics	Data localisation and digital-sovereignty legislation	Near-total foreign-platform dependency; no data law	Pass data-sovereignty legislation; fund Azerbaijani AI data (P2-P3)
Environment	Binding energy-efficiency standards (IEA)	No AI environmental-reporting requirement	Adopt IEA standards; build climate-finance mechanisms (P5)

Source: author's analysis, drawing on the EU AI Act (2024) [27]; Global Digital Compact (2024) [30]; IEA [6]; OECD [16].

3.5 Five principles for equitable AI governance

A problem of this scale calls for governance designed to match it. The five principles below are not aspirations; each answers a documented gap and points to a concrete next step. The question of how AI comes to count as public infrastructure, and which cultural and institutional conditions allow that to happen in transitional economies, has itself become a subject of regional scholarship [31]. Table 5 summarises the principles with their application to Azerbaijan.

Table 5. *Five principles for equitable AI governance with Azerbaijan-specific applications.*

Principle	Core content	Azerbaijan application
P1. Universal access	AI infrastructure as a public good; universal-service mandates; state investment in underserved communities	ASAN is a proven precedent that targets public investment works. Extend the model to AI-powered public services at scale.
P2. Data sovereignty	Community rights over locally generated data; required representation of minority languages in training datasets	Addresses the underrepresentation of Azerbaijani in AI corpora, a gap with concrete performance consequences. National data sovereignty legislation is needed.
P3. Representative development	Public investment in local AI research capacity; linguistically diverse training data as a public good	Fund Azerbaijani, Georgian, and Armenian training data as a regional public good; build indigenous research capacity.
P4. Algorithmic accountability	Mandatory impact assessments for high-risk AI; independent audit rights; a genuine right of redress	Critical as AI enters ASAN services. Adopt the EU AI Act framework before deployment expands further.
P5. International cooperation	Binding multilateral frameworks; equitable technology transfer; redress for asymmetric environmental costs	Active engagement in the Global Digital Compact and EU AI Act processes would strengthen governance capacity and amplify Azerbaijan's voice.

Source: author's framework, drawing on [3], [6], [27], [30].

3.6 Limitations

A few limitations should be kept in view. The Azerbaijan adoption numbers in Table 2 and Figure 2 are estimates, inferred from the country's regional position rather than measured in a dedicated national survey, so they are best read as indicative. Several of the headline indicators, too, come from institutional reports and industry trackers rather than peer-reviewed studies; this grey literature is current but not refereed, and it was used only where no comparable academic dataset exists, with the source named each time. Finally, this is a single-author synthesis of a field that keeps moving. The screening followed PRISMA principles but does not extend to a full meta-analysis with a stage-by-stage exclusion diagram, and the newest figures will keep shifting. None of these changes the direction the evidence points in, but each marks a spot where a reader should stay cautious and where later work could add precision.

4. Conclusion

Read together, the five dimensions all point one way. Adoption in the Global North is running about three-quarters ahead of the Global South, and the lead is stretching [8]. Around 92 million jobs are set to go by 2030, mostly in lower-income countries, while the bulk of the 170 million new one lands where the infrastructure already is [5]. The gap in facial-recognition accuracy is no glitch; it follows how the systems were put together [18]. Most of the world's cloud capacity sits with a handful of firms, and smaller states lean on them by default [28]. And the environmental bill falls hardest on the people who get the least out of the technology [6].

For Azerbaijan, none of these stays abstract. It shows up in tools that handle Azerbaijani badly, in outsourcing and clerical staff who face automation with nowhere obvious to retrain, in public services that already lean on automated decisions while no one can be held to account for them, and in a near-total dependence on foreign AI platforms. As the UNDP warned in late 2025, without deliberate choices AI could undo half a century of development gains [3].

The picture is not uniformly bleak. Mongolia, for one, has launched a National AI Programme that is training thousands of teachers and specialists across all twenty-one of its provinces, with the stated aim of widening access and closing the gap between town and countryside [32]. Its home-grown Mongolian-language model, Egune, is a reminder that a smaller country can build for a low-resource language directly instead of waiting on foreign systems [33], which is exactly the step Azerbaijan will need to take for Azerbaijani. Bhutan has gone a similar route, standing up a national AI laboratory and development centre to grow capability at home rather than buy it in wholesale [34]. And Azerbaijan has already shown, with ASAN, that patient public investment in digital services can reach people fairly. The thread running through these cases is plain enough: inclusive AI is not really waiting on a technical breakthrough. It is waiting on choices.

Those choices are what the paper is finally about. The AI Divide was built out of decisions, about who funds the technology, whose data trains it, who writes its rules, and who is in the room when those rules are written, and decisions of that kind can be taken differently. The five principles offered here are a place to start, not a finished blueprint. The room to act on them is open today; whether it stays open is not guaranteed.

Acknowledgment

The author thanks the United Nations Development Programme, the International Energy Agency, the World Economic Forum, the International Labour Organization, Stanford University's Human-Centered AI institute, Oxford Insights, and the Microsoft AI Economy Institute for the open-access data and reports drawn on in this study. A condensed version of this work was presented at the IV International Conference on Modern Trends in Digital Economy (DEMCRO 2026) at UNEC, Baku, in April 2026; that conference paper and the present manuscript are related but separate contributions, and this manuscript is the full research submission. Generative AI tools were used for language editing and formatting; the author reviewed and verified all content and took full responsibility for it.

Authors' Declaration

Conflicts of Interest: The author declares no conflict of interest. Funding: No external funding was received for this study.

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