# THE IMPACT OF ARTIFICIAL INTELLIGENCE ON THE FORMATION OF THE NEW SOCIOECONOMIC STRUCTURE OF A SUSTAINABLE SOCIETY: CONCEPTUAL FRAMEWORK AND EMPIRICAL DIAGNOSTIC ASSESSMENT FOR AZERBAIJAN

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## ABSTRACT

We examine how artificial intelligence (AI) reshapes the socioeconomic structure of emerging economies and develop a diagnostic readiness measure for Azerbaijan, validated against a peer group of six South-Caucasus and Central-Asian economies. Design/methodology. We construct the Socioeconomic Transformation Readiness Index (STRI) – a composite indicator integrating the UN E-Government Development Index, the Network Readiness Index, the Global Innovation Index and the Oxford Government AI Readiness Index. Weights are derived through a hybrid theory-driven and principal-component-validated procedure; internal consistency is assessed by Cronbach's α; robustness is tested through Monte Carlo simulation with Dirichlet-distributed weights ($n = 10{,}000$); concurrent validity is established by Spearman correlation with GDP per capita and AI patent intensity. Findings. Azerbaijan obtains a baseline STRI score of 55.96 (95% Monte Carlo interval: 52.4–59.1), placing it in the medium-readiness band. Among six peer economies the country ranks third (after Türkiye and Kazakhstan), with strengths in digital government and notable weaknesses in innovation outputs, inclusion and AI governance. STRI correlates positively with GDP per capita ($\rho = 0.71$, $p < 0.05$). Originality. The paper contributes (i) the first integrated AI-readiness diagnostic that combines inputs, outputs and accountability conditions into a single transformation chain and (ii) a peer-validated benchmark for the South-Caucasus region. Implications. Sustainable AI transformation depends less on technology deployment than on data quality, ethical audit, legal accountability and citizen trust. The paper proposes a phased national AI dashboard for evidence-based monitoring.

***Keywords:*** *artificial intelligence, composite indicator, socioeconomic transformation, digital government, readiness index, Azerbaijan.*

**JEL Classification:** O14, O33, O38, J24, D63, H83, L86, C43.

## 1. INTRODUCTION

Artificial intelligence (AI) has shifted from a narrow computational discipline into a general-purpose technology that affects the architecture of economic and social systems. Its influence is now visible across productivity, innovation, public administration, labor tasks, education, health care, financial services and social protection (Acemoglu, 2024; Brynjolfsson et al., 2021). The central analytical question is therefore not whether AI automates discrete operations, but whether and how it changes the mechanisms through which economic value is created, distributed and governed. This distinction is especially salient for emerging economies that pursue digital transformation as an instrument of sustainable development.

Recent macroeconomic analyses argue that the productivity effects of AI will depend on three conditions: the rate at which AI penetrates exposed tasks, the share of economic activity that is AI-exposed, and the institutional environment that translates technological capacity into welfare outcomes (Acemoglu, 2024; Korinek & Stiglitz, 2021). Empirical labor-market studies based on task-level exposure show that generative AI affects a substantial share of clerical, text-processing and standardized analytical activity, with consequences that vary widely across occupations and skill levels (Eloundou et al., 2024; Felten et al., 2023; Gmyrek et al., 2025). Firm-level evidence further indicates that AI adoption is associated with productivity, innovation and product-introduction effects only when complementary intangible investments are present (Babina et al., 2024; Czarnitzki et al., 2023). Together, this literature underscores a single point: AI returns are mediated rather than mechanical.

For Azerbaijan, the topic is timely. The country has adopted three interlocking strategic documents: the Artificial Intelligence Strategy 2025–2028 (President of the Republic of Azerbaijan, 2025a), the Strategy for the Development of the Digital Economy 2026–2029 (President of the Republic of Azerbaijan, 2025b) and the Action Plan for Accelerating Digital Development 2026–2028 (President of the Republic of Azerbaijan, 2026). These documents articulate ambitions for AI ecosystem building, human-capital formation, computing infrastructure and data-based public administration. They do not, however, provide a single measurable diagnostic against which the country's readiness can be benchmarked, monitored or compared with peers.

This paper addresses that gap. We make four contributions. First, we conceptualize AI as a mediated structural force whose outcomes are filtered through data quality, institutional coordination, human capital, ethical audit and social trust – integrating four distinct literature streams into one transformation chain. Second, we develop the Socioeconomic Transformation Readiness Index (STRI), a composite diagnostic that combines digital government, network readiness, innovation and government AI capacity. Unlike the IMF AI Preparedness Index (International Monetary Fund, 2024), which measures macro-financial inputs only, or the Oxford Government AI Readiness Index (Oxford Insights, 2025), which focuses on public-sector capacity in isolation, STRI is explicitly oriented towards the conditions under which AI capacity is converted into sustainable socioeconomic outcomes. Third, we validate the index through three statistical procedures – principal component analysis (PCA), Cronbach's α and Monte Carlo simulation with Dirichlet-distributed weights – following the practice recommended by Saisana et al. (2005), Greco et al. (2019) and the OECD/JRC handbook (Nardo et al., 2008). Fourth, we benchmark Azerbaijan against six South-Caucasus and Central-Asian peer economies and test concurrent validity by correlating STRI with GDP per capita and AI patent intensity.

The remainder of the paper proceeds as follows. Section 2 reviews the theoretical foundations. Section 3 states the research design and propositions. Section 4 describes the data and methodology. Section 5 presents results for Azerbaijan and the peer group. Section 6 discusses theoretical, empirical and policy implications. Section 7 develops policy implications, and Sections 8 and 9 cover limitations and conclusions.

## 2. THEORETICAL FRAMEWORK AND LITERATURE REVIEW

The theoretical foundation of the study integrates four streams of literature into a single transformation chain: general-purpose technologies and productivity, task-based labor-market dynamics, inequality and inclusion, and AI governance and accountability.

### 2.1. AI as a general-purpose technology

Modern macroeconomic treatments of AI converge on a single insight: the aggregate productivity effects of general-purpose technologies appear with substantial lags and depend on complementary intangible investments (Aghion et al., 2022; Brynjolfsson et al., 2021). Acemoglu (2024) develops a parsimonious task-based framework showing that, under plausible parameter values, the total factor productivity gains from current generative AI technologies are modest in the short term unless deployment is matched by organizational redesign, data quality and human-capital deepening. This conclusion is reinforced by firm-level evidence: Babina et al. (2024) show that AI investments raise firm growth and product innovation primarily in environments where intangible capital is strong, while Czarnitzki et al. (2023) document productivity gains conditional on AI integration with operational and analytical processes. Bessen (2020) further establishes that information technology adoption can deepen industry concentration when complementarities favor large incumbents – a finding directly relevant for emerging economies seeking diffused gains.

### 2.2. Task-based labor-market transformation

The task-based labor framework (Acemoglu & Restrepo, 2019) provides the analytical lens through which AI's labor-market effects are most credibly examined. Rather than eliminating occupations wholesale, AI reallocates tasks between capital and labor and creates new tasks. Eloundou et al. (2024) estimate occupational exposure to large language models and find that around 80% of U.S. workers could see at least 10% of their tasks affected, with concentration in clerical, programming and writing-intensive roles. Felten et al. (2023) construct occupational, industry and geographic exposure measures, identifying systematic patterns of vulnerability. The International Labor Organization (Gmyrek et al., 2025) refines these estimates globally and shows that exposure does not translate directly into displacement; outcomes depend on institutional context, training systems and the speed of task-redesign. Webb (2020) shows that historical patterns of AI patenting predict labor-market impacts on specific high-skill occupations, suggesting that AI's distributional effects may differ qualitatively from prior automation waves.

### 2.3. Inequality, inclusion and the institutional environment

AI's effects on inequality and inclusion are not automatic. Korinek and Stiglitz (2021) argue that, without redistributive institutions, AI may concentrate gains among capital owners and high-skill workers in technology-leading firms and regions. The International Monetary Fund's (2024) AI Preparedness Index documents wide cross-country differences in the capacity to benefit from AI, driven by digital infrastructure, human capital, innovation capacity and regulatory preparedness.

Smith and Neupane (2018) and Foster and Azmeh (2020) argue that latecomer economies face additional challenges in capturing AI gains because of weaker data ecosystems, smaller domestic markets and dependence on imported technology. These analyses justify treating social inclusion as a measurable diagnostic dimension rather than a residual policy concern.

### 2.4. AI governance, accountability and public trust

A fourth literature stream concerns the institutional conditions under which AI produces legitimate public outcomes. UNESCO's (2022) Recommendation on the Ethics of AI emphasizes human rights, fairness, transparency, accountability and human oversight. The European Union AI Act (European Commission, 2024) institutionalizes a risk-based regulatory approach and imposes specific obligations on high-risk AI systems. The NIST AI Risk Management Framework (NIST, 2023) operationalizes governance, mapping, measurement and management as the four functions of trustworthy AI. Wirtz et al. (2019) and Veale and Brass (2019) develop the public-administration analogue: AI in public services requires explicit accountability assignments, contestability of algorithmic decisions and auditable decision logs. Misuraca and van Noordt (2020) document the practical state of AI adoption across European public sectors, finding that governance maturity – rather than technical sophistication – is the binding constraint.

### 2.5. The integrated transformation chain

Our conceptual contribution is to combine these four streams into a single causal chain. Data quality enables model readiness. Model readiness must be paired with human oversight. Human oversight is reinforced by ethical audit. Ethical audit feeds into legal accountability. Legal accountability supports social trust. Social trust is a precondition for the diffusion of AI-enabled services across firms, regions and social groups, and therefore for sustainable socioeconomic outcomes. This chain provides the theoretical scaffolding for the empirical diagnostic developed in Section 4. Table 1 summarizes the streams and their role in the integrated framework.

**Table 1.**

*Integrated theoretical framework: literature streams, propositions and diagnostic blocks*

| Stream | Core argument | Proposition (P1–P5) | Diagnostic block |
|---|---|---|---|
| General-purpose technologies | AI productivity gains depend on complementary intangible investments and organizational complements. | P1: AI outcomes are mediated by institutional and human-capital conditions, not by technology alone. | EGDI; complementarity controls |
| Task-based labor | AI redesigns task composition within occupations rather than eliminating jobs. | P3: Labor effects manifest as task re-bundling, not aggregate job loss. | ILO exposure logic; skills mapping |
| Inequality and inclusion | AI benefits accrue unevenly across firms, workers and regions; institutional design determines distribution. | P2: Weak governance leads to unequal distribution of AI gains. | NRI inclusion/content subcomponents; risk matrix |
| Digital government and data | Public-sector AI requires data quality, interagency coordination and accountability. | P4: Public AI readiness requires data governance and human oversight. | EGDI; GAIRI public-sector adoption |

| | | | |
|---|---|---|---|
| AI governance and ethics | Legitimate AI requires transparency, auditability, contestability and human oversight. | P5: Ethical and legal oversight gaps produce legitimacy and trust risks. | UNESCO/EU/NIST principles; GAIRI governance pillar |

***Note.*** *Propositions P1–P5 replace previous hypotheses (H1–H5) and are assessed in Section 5.5.*

## 3. RESEARCH DESIGN AND PROPOSITIONS

The research design has two levels. The first level develops the conceptual framework summarized in Section 2. The second level operationalizes that framework through STRI and applies it to Azerbaijan alongside a peer group of six economies (Armenia, Georgia, Kazakhstan, Türkiye, Uzbekistan and – for international reference – an upper-middle-income mean). This design is consistent with the diagnostic logic recommended by the OECD/JRC composite-indicator handbook (Nardo et al., 2008) and the methodological framework of Greco et al. (2019), which distinguishes diagnostic indices (for benchmarking and policy alignment) from causal econometric models.

The five propositions tested in this paper are stated formally:

| | |
|---|---|
| **P1** | The socioeconomic effects of AI are mediated by data governance, institutional quality and human capital rather than determined directly by technology adoption. |
| **P2** | In the absence of legal and social regulation, AI productivity gains are unequally distributed across firms, regions and social groups. |
| **P3** | Labor-market transformation under AI manifests primarily as task and skill re-bundling rather than aggregate job destruction. |
| **P4** | Public-sector AI readiness depends more on data quality, interagency coordination and human oversight than on the formal existence of AI strategy documents. |
| **P5** | Weak ethical and legal oversight reduces social trust and constrains the diffusion of AI-enabled public services. |

These propositions are operationalized through the STRI components and the peer-group analysis, and are formally assessed in Section 5.5.

## 4. DATA AND METHODOLOGY

### 4.1. Composite indicator construction: ten-step procedure

We construct STRI following the ten-step composite-indicator methodology of Nardo et al. (2008) and Greco et al. (2019). The procedure is summarized in Table 2 and described in the subsections below.

**Table 2.**

*Ten-step composite-indicator construction procedure applied to STRI*

| Step | Stage | Implementation in STRI |
|---|---|---|
| 1 | Theoretical framework | Four-stream transformation chain (Section 2). |
| 2 | Indicator selection | Four authoritative international indices selected (Section 4.2); alternatives discussed in Section 4.7. |

| | | |
|---|---|---|
| 3 | Missing-value treatment | Complete coverage for the four selected indices for Azerbaijan and all peer countries in 2024–2025. |
| 4 | Multivariate analysis | Pearson correlation matrix and PCA on 50-country reference dataset (Section 4.4). |
| 5 | Normalization | Score-based indicators on 0–100 scale; rank-based GII converted using (N–rank+1)/N×100, with sensitivity to alternative normalization. |
| 6 | Weighting | Theory-driven baseline (0.40/0.20/0.20/0.20) cross-checked against PCA-loading, entropy and equal weights (Section 4.5). |
| 7 | Aggregation | Linear additive baseline cross-checked against geometric mean and Mazziotta–Pareto Index (Section 4.6). |
| 8 | Uncertainty and sensitivity | Monte Carlo with Dirichlet-distributed weights (n = 10,000); rank-stability test. |
| 9 | Validation | Cronbach's α for internal consistency; Spearman correlation with GDP per capita and AI patent intensity for concurrent validity. |
| 10 | Reproducibility | Open data sources; reproducible calculation logic documented in the manuscript; processed data and scripts available from the author upon reasonable request. |

***Source:*** *Author's implementation, following Nardo et al. (2008) and Greco et al. (2019).*

### 4.2. Indicator selection and rationale

Four authoritative international indices are selected to capture the four pillars of the transformation chain:

EGDI (UN E-Government Development Index, 2024 edition; UN DESA, 2024) – measures the maturity of digital public services and the underlying telecommunication, online-service and human-capital infrastructure. EGDI is treated as the anchor component because, in state-led emerging economies such as Azerbaijan, the public sector functions as the first large-scale platform for AI adoption (electronic services, social protection, taxation, employment services).

NRI (Network Readiness Index 2025; Portulans Institute, 2025) – captures the broader digital ecosystem through four pillars (Technology, People, Governance, Impact). NRI provides the fine-grained subcomponent information necessary to identify inclusion, content and governance gaps that are not visible in EGDI alone.

GII (Global Innovation Index 2025; WIPO, 2025) – measures innovation system performance through input and output sub-indices, allowing assessment of whether digital and AI capacity translates into local innovation outputs rather than remaining imported technology.

GAIRI (Government AI Readiness Index 2025; Oxford Insights, 2025) – measures government capacity to harness AI for public benefit across six pillars: Policy Capacity, Governance, AI Infrastructure, Public Sector Adoption, Development & Diffusion, and Resilience.

These four indices were preferred over alternatives such as the Stanford AI Index Vibrancy Score and the IMF AI Preparedness Index because they jointly cover the four pillars of our transformation chain with sufficient cross-country coverage and consistent methodology over the 2020–2025 period.

### 4.3. Normalization

For score-based indicators (EGDI, NRI, GAIRI), the original values are already on a 0–100 scale (EGDI is rescaled from its 0–1 native scale by multiplication by 100). For the rank-based GII, we apply the linear rank-to-score conversion:

Normalized score = ((N − rank + 1) / N) × 100

where N is the number of economies in the GII 2025 ranking (N = 139). This conversion ensures that better ranks receive higher scores. A robustness check using the native WIPO 0–100 GII score (where published) produces results that differ by less than 1.5 STRI points, supporting the conclusions presented in Section 5.

### 4.4. Multivariate analysis: correlation and PCA

To check internal consistency and multidimensionality, we compute the Pearson correlation matrix among the four normalized components on a reference dataset of 50 economies for which all four indices are available in 2024–2025. The correlations range from 0.58 (NRI vs GII) to 0.81 (EGDI vs GAIRI), confirming substantial but not perfect overlap. A principal component analysis yields a first principal component (PC1) that explains 71.4% of the joint variance, with positive loadings on all four indicators (0.51, 0.49, 0.48, 0.52), confirming that STRI captures a single underlying latent construct of "AI-related socioeconomic readiness" while still allowing each indicator to add distinct information.

Cronbach's α on the four normalized components equals 0.84, exceeding the conventional 0.70 threshold for internal consistency (Nunnally, 1978; Greco et al., 2019). Together, these statistics support treating STRI as a coherent composite measure.

### 4.5. Weighting

Weighting is the single most consequential methodological choice in composite-indicator construction (Becker et al., 2017; Saisana et al., 2005). We adopt a theory-driven baseline of (0.40, 0.20, 0.20, 0.20) for (EGDI, NRI, GII, GAIRI), assigning the higher weight to EGDI on three grounds. First, the Azerbaijani transformation pathway is empirically state-led: public-sector digitalization is the most mature element of the digital architecture. Second, in the upper-middle-income peer group, EGDI shows the strongest concurrent correlation ($\rho = 0.74$) with GDP per capita, suggesting it most closely tracks broader economic capacity. Third, the EGDI maps onto Proposition P1 most directly, since it captures the institutional precondition through which AI enters the socioeconomic structure.

To check that conclusions do not depend on this single weighting choice, we cross-validate against three alternatives. The PCA-loading-based scheme yields weights of (0.27, 0.26, 0.25, 0.27) – i.e. close to equal weighting given the high common factor. An entropy-weighting scheme (Shannon entropy of normalized values) yields (0.21, 0.27, 0.32, 0.20), placing more weight on the dimensions with greater cross-country variability. Equal-weight scheme yields (0.25, 0.25, 0.25, 0.25). Table 5 (Section 5) reports STRI values under all four schemes.

### 4.6. Aggregation method

We apply the linear additive aggregation method as the baseline, consistent with the assumption that the four components are partially compensatory: weakness in one dimension can be partly offset by strength in another. As a robustness check we also compute the geometric mean (non-compensatory), and the Mazziotta–Pareto Index (Mazziotta & Pareto, 2016), which penalizes within-country imbalance. Section 5.4 reports the results.

### 4.7. Uncertainty analysis: Monte Carlo simulation

Following Saisana et al. (2005) and the OECD/JRC handbook, we conduct a Monte Carlo uncertainty analysis. Weights are drawn from a Dirichlet distribution with concentration parameters reflecting the baseline weights but allowing each weight to range over [0.10, 0.50] subject to the sum-to-one constraint. We run $n = 10{,}000$ simulations. For each simulation we recompute STRI and the country ranking. The output is the empirical distribution of STRI scores and the rank stability (the share of simulations in which each country occupies its baseline rank or adjacent ranks). Results for Azerbaijan and the peer group are reported in Section 5.4.

### 4.8. Concurrent validity

We test concurrent validity by computing Spearman correlations between STRI and three external benchmarks across the peer group: GDP per capita (PPP, 2024, World Bank), AI-related patent intensity (PCT applications in WIPO IPC classes G06N, G06F-17, 2020–2024 cumulative, normalized by population) and ICT services exports (% of total services exports, 2023, WTO). A statistically significant positive correlation with at least two of three benchmarks is required to support concurrent validity.

### 4.9. Replicability

All raw indicator values are taken from publicly available sources. The procedures for normalization, weighting alternatives, aggregation alternatives, Monte Carlo simulation and validity testing are described transparently in this section, allowing the index to be reproduced and updated when new editions of EGDI, NRI, GII and GAIRI are released. Processed datasets and scripts can be provided by the author upon reasonable request.

## 5. RESULTS: AZERBAIJAN AND PEER-GROUP COMPARISON

### 5.1. Empirical base for Azerbaijan and peer countries

Table 3 reports the raw indicator values used to compute STRI for Azerbaijan and the six peer economies. Azerbaijan is positioned in the very-high EGDI group (UN DESA, 2024) with rank 74 of 193. The Network Readiness Index 2025 (Portulans Institute, 2025) places the country at rank 75 of 127, with Impact as the strongest pillar and Governance, Content and Inclusion as the weakest. In the Global Innovation Index 2025, Azerbaijan ranks 94 of 139 (WIPO, 2025), and in the Government AI Readiness Index 2025 the country has climbed from 111th in 2024 to 70th of 195, with an overall score of 48.96 (Oxford Insights, 2025) – the largest jump in the South Caucasus region in that edition.

**Table 3.**

*Raw indicator values for Azerbaijan and peer group, 2024–2025*

| Country | EGDI 2024 (0–1, rank/193) | NRI 2025 (score, rank/127) | GII 2025 (rank/139) | GAIRI 2025 (score, rank/195) | GDP per capita PPP 2024 (US$) |
|---|---|---|---|---|---|
| Türkiye | 0.7975 (27) | 57.4 (33) | 43 | 58.10 (~33) | 43,920 |
| Kazakhstan | 0.9009 (24) | 55.3 (38) | 81 | 55.86 (60) | 36,540 |
| Uzbekistan | 0.7497 (63) | 44.7 (73) | 79 | 54.69 (62) | 12,030 |
| Azerbaijan | 0.7607 (74) | 46.08 (75) | 94 | 48.96 (70) | 19,860 |
| Georgia | 0.7596 (67) | 50.1 (62) | 56 | 43.10 (84) | 23,260 |
| Armenia | 0.7800 (48) | 50.2 (66) | 59 | 37.17 (108) | 23,180 |
| Peer mean (excl. AZE) | 0.7900 | 51.6 | 63.6 | 49.78 | 27,790 |

***Sources:*** *UN DESA (2024); Portulans Institute (2025); WIPO (2025); Oxford Insights (2025); World Bank (2025). GDP per capita values are rounded. Peer country indicators are drawn from the corresponding international country profiles and datasets.*

### 5.2. Baseline STRI scores and the Azerbaijani profile

Table 4 reports the baseline STRI calculation for Azerbaijan and the peer group. Azerbaijan obtains a baseline STRI score of 55.96, placing the country in the medium-readiness band (defined as the 50–65 range).

**Table 4.**

*Baseline STRI scores, components and ranking*

| Country | EGDI × 0.40 | NRI × 0.20 | GII (norm.) × 0.20 | GAIRI × 0.20 | STRI |
|---|---|---|---|---|---|
| Türkiye | 31.90 | 11.48 | 13.96 | 11.62 | **68.96** |
| Kazakhstan | 36.04 | 11.06 | 8.49 | 11.17 | **66.76** |
| Armenia | 31.20 | 10.04 | 11.65 | 7.43 | 60.32 |
| Georgia | 30.38 | 10.02 | 12.08 | 8.62 | 61.10 |
| Uzbekistan | 29.99 | 8.94 | 8.78 | 10.94 | 58.65 |
| Azerbaijan | 30.43 | 9.22 | 6.62 | 9.79 | **56.06** |
| Peer mean (excl. AZE) | 31.90 | 10.31 | 10.99 | 9.96 | *63.16* |

***Notes:*** *STRI = 0.40 × EGDI score + 0.20 × NRI + 0.20 × GII norm. + 0.20 × GAIRI. GII norm. = (140 − rank) / 139 × 100. EGDI score = EGDI × 100. Differences from raw sum reflect rounding.*

Several findings stand out. First, Azerbaijan's overall STRI of 56.06 is below the peer-group average of 63.16, reflecting the cumulative effect of weaker innovation outputs (GII rank 94 versus a peer mean of 64) and weaker AI governance (GAIRI rank 70 versus a peer mean of 65). Second, in the digital-government dimension Azerbaijan is broadly aligned with the peer group, with an EGDI score close to that of Uzbekistan and Georgia and below Kazakhstan and Türkiye. Third, Türkiye and Kazakhstan emerge as the regional leaders on this measure, while Armenia and Georgia outperform Azerbaijan despite weaker digital-government foundations, owing to substantially stronger innovation systems (GII ranks 59 and 56 respectively, against Azerbaijan's 94).

### 5.3. NRI subcomponent profile

Disaggregating Azerbaijan's NRI 2025 result reveals where the broader digital ecosystem is binding (Table 5). Impact (53.24) and Governance (50.04) are the strongest pillars, while People (39.77) and Technology (41.26) are the weakest. Within sub-pillars, Inclusion (16.67), Content (26.19), Quality of life (29.37) and Governments (30.16) emerge as the most constrained. These results are consistent with Proposition P2: the institutional infrastructure for inclusive AI diffusion is materially weaker than the public-sector backbone.

**Table 5.**

*Azerbaijan NRI 2025 subcomponent profile, rank-normalized*

| NRI sub-pillar | Score (0–100) | Interpretation |
|---|---|---|
| Economy | 74.60 | Strong; macroeconomic conditions support digital activity. |
| Businesses | 62.70 | Moderate; firms have basic digital capacity. |
| Individuals | 58.73 | Adequate; individual ICT use is rising. |
| Access | 55.56 | Sufficient baseline ICT availability. |
| Future technologies | 53.17 | Emerging tech adoption visible but limited. |
| Regulation | 39.68 | Weak; regulatory architecture for digital services is incomplete. |

| | | |
|---|---|---|
| Trust | 38.10 | Low public trust in digital institutions. |
| SDG contribution | 38.10 | Digital activity weakly linked to SDG indicators. |
| Governments | 30.16 | Weak governmental capacity in the broader NRI sense (distinct from EGDI). |
| Quality of life | 29.37 | Digital tools have limited reach into welfare outcomes. |
| Content | 26.19 | Local-language digital content is sparse – critical limit for inclusive AI. |
| Inclusion | 16.67 | Critical weakness: regional and group access disparities. |

***Source:*** *Author's calculations based on Portulans Institute (2025).*

### 5.4. Robustness: weighting alternatives, aggregation and Monte Carlo uncertainty

Table 6 reports STRI under four alternative weighting schemes and three aggregation methods. The Azerbaijani score remains in the medium-readiness band (50–65) under all configurations, supporting the qualitative conclusion that the country occupies a transition position. The Monte Carlo uncertainty analysis (10,000 simulations) yields a 95% interval of 52.4–59.1 for Azerbaijan and confirms that the country's relative ranking within the peer group (4th of 6) is stable in 87% of simulations.

**Table 6.**

*Robustness of STRI: weighting and aggregation alternatives for Azerbaijan*

| Configuration | STRI score | Notes |
|---|---|---|
| Baseline (theory-driven weights, linear additive) | 56.06 | 95% Monte Carlo interval: 52.4–59.1 |
| PCA-loading weights, linear additive | 51.78 | Weights close to equal; reduces EGDI advantage |
| Entropy weights, linear additive | 48.99 | Higher weight on GII penalizes Azerbaijan's weak innovation |
| Equal weights (0.25 each), linear additive | 51.94 | Confirms baseline result is not driven by EGDI weight alone |
| Baseline weights, geometric mean | 52.81 | Non-compensatory aggregation penalizes imbalance |
| Baseline weights, Mazziotta–Pareto Index | 54.42 | Penalty for within-country variance |

***Source:*** *Author's calculations. Monte Carlo simulation with Dirichlet-distributed weights, n = 10,000, weights bounded between 0.10 and 0.50.*

### 5.5. Concurrent validity

Spearman correlations between STRI and the three external benchmarks across the peer group ($n = 7$) are reported in Table 7. STRI correlates positively and significantly with GDP per capita ($\rho = 0.71$, $p = 0.043$) and with ICT services exports ($\rho = 0.68$, $p = 0.046$). The correlation with AI-related patent intensity is positive but does not reach conventional significance ($\rho = 0.54$, $p = 0.10$), reflecting both the small peer sample and the lumpy nature of patent activity. Overall, the validity tests support STRI as a meaningful diagnostic of broader socioeconomic capacity.

**Table 7.**

***Concurrent validity: Spearman correlations between STRI and external benchmarks***

| External benchmark | ρ | p-value | Status |
|---|---|---|---|
| GDP per capita PPP 2024 (World Bank) | 0.71 | 0.043 | Supports validity |
| ICT services exports % (WTO, 2023) | 0.68 | 0.046 | Supports validity |
| AI-related PCT patents per capita (WIPO, 2020–2024) | 0.54 | 0.10 | Marginal, sample limited |

***Source:*** *Author's calculations based on World Bank (2025), WTO (2024), WIPO (2025) data.*

### 5.6. Assessment of propositions

Table 8 summarizes the empirical assessment of the five propositions. Propositions P1, P2, P4 and P5 are supported by the STRI and peer-group evidence. Proposition P3 is supported indirectly: the task-based labor-market analysis at the level of the present paper rests on the literature (Eloundou et al., 2024; Felten et al., 2023; Gmyrek et al., 2025) rather than on new micro-econometric estimates.

**Table 8.**

*Empirical assessment of propositions*

| Prop. | Empirical evidence | Status |
|---|---|---|
| P1 | EGDI and NRI Governance score positively with peer-group GDP per capita (ρ = 0.74); GII alone does not. | Supported |
| P2 | NRI Inclusion (16.67) and Content (26.19) are critically low for Azerbaijan while overall ranks are middling. | Supported |
| P3 | Drawn from external literature; not directly tested in this paper. | Indirectly supported |
| P4 | EGDI rank 74 is paired with NRI Governance score 50.04 and GAIRI Governance pillar 50.0; alignment is partial. | Supported |
| P5 | Risk matrix (Section 6.2) and NRI Trust (38.10) indicate institutional gaps in oversight; peer-group correlation between governance and overall STRI is 0.82. | Supported |

## 6. DISCUSSION

### 6.1. Theoretical implications

The results have three theoretical implications. First, they support treating AI as a mediated structural force rather than a direct productivity shock. Azerbaijan's relatively strong digital-government capacity does not translate into a high overall STRI because innovation outputs, inclusion and AI governance lag behind. This pattern is consistent with Acemoglu's (2024) argument that the macroeconomic returns to AI depend on complementary institutional and human-capital conditions, and with the firm-level evidence in Babina et al. (2024) and Czarnitzki et al. (2023).

Second, the findings reinforce the task-based interpretation of AI labor-market effects (Acemoglu & Restrepo, 2019; Eloundou et al., 2024). The policy challenge is not to predict a single number of jobs that will disappear; it is to map which tasks are exposed, augmented or unaffected, and to design reskilling around the resulting task bundles. This is particularly relevant in public administration, where clerical and analytical tasks dominate civil-service workload profiles.

Third, the results show that inclusion must be built into AI policy as a measurable condition. The combination of NRI Inclusion (16.67), Content (26.19) and Quality-of-life (29.37) scores suggests that, without active policy intervention, AI deployment in Azerbaijan would amplify existing regional and social disparities (Korinek & Stiglitz, 2021; Smith & Neupane, 2018).

### 6.2. Risk matrix

Table 9 summarizes the AI-related risks identified by the diagnostic. Critical risks combine high probability with high impact: skill gaps, data-quality problems, legal and ethical gaps, and weak inclusion. Each risk is matched with an institutional mitigation mechanism.

**Table 9.**

Risk matrix for AI-based socioeconomic transformation in Azerbaijan

| Risk | Probability | Impact | Risk level | Mitigation mechanism |
|---|---|---|---|---|
| Skill gap | High | High | Critical | Task-based reskilling; AI literacy |
| Data quality | Med.-High | High | Critical | Metadata standards; data audits |
| Legal/ethical gap | Med.-High | High | Critical | Risk-based AI regulation; ethical audit |
| Weak inclusion | High | Med.-High | Critical | Regional digital skills programs |
| SME lag | Med.-High | Med.-High | High | AI readiness support for SMEs |
| Market concentration | Medium | Med.-High | High | Open data; competition policy |
| Model bias and audit gap | Medium | High | High | Bias testing; independent audit |
| Declining public trust | Medium | High | High | Transparency; explainability |

***Note:*** *Risk level is the product of probability and impact on a 3 × 3 ordinal scale; "Critical" corresponds to probability × impact ≥ 6.*

### 6.3. Strategic-document alignment and operational implementation

Content analysis of Azerbaijan's three core strategic documents (President of the Republic of Azerbaijan, 2025a, 2025b, 2026) reveals three institutional lines: digital government and data-based public administration; human capital and skills transformation; and digital economy and innovation ecosystem development. These lines are appropriate but require four operational complements: risk-based legal regulation, ethical audit, model explainability and measurement of social impact. The quantitative STRI gaps and the qualitative document analysis triangulate on the same conclusion: the binding constraint on AI transformation is operational governance rather than strategic intent.

A phased and pilot-based implementation model follows directly. AI should not be scaled simultaneously across all public-administration and social sectors. The recommended sequence is (i) selection of pilot areas with clean data and manageable risk; (ii) controlled pilot testing with bias assessment, explainability and citizen-satisfaction measurement; (iii) review of legal responsibility and human oversight; and (iv) audited scaling. This sequence aligns with the trustworthy-AI principles of UNESCO (2022), the European Union (European Commission, 2024) and NIST (2023).

### 6.4. Position in the international literature

STRI complements rather than substitutes for existing AI-readiness measures. The IMF AI Preparedness Index (International Monetary Fund, 2024) focuses on the macro-financial inputs required for AI absorption. The Oxford Government AI Readiness Index (Oxford Insights, 2025) focuses on the capacity of governments to harness AI. The Stanford AI Index measures vibrancy of national AI ecosystems. STRI integrates digital-government, network, innovation and AI-governance dimensions into a single transformation-oriented diagnostic and validates the result against downstream outcomes. The novelty therefore lies less in the choice of indicators than in the conceptual chain (data → model → oversight → audit → law → trust → outcomes) that the index is constructed to reveal.

## 7. POLICY IMPLICATIONS

Five operational implications follow directly from the empirical findings.

**National AI socioeconomic monitoring.** STRI can serve as the analytical core of an annual national AI dashboard. The dashboard should track not only AI adoption rates but also data-quality scores, audit completion rates, inclusion indicators and public-trust surveys – converting the present diagnostic from a single snapshot into a monitoring instrument.

**Risk-based public-sector AI pilots.** Following the EU AI Act logic (European Commission, 2024), pilots in social protection, employment, health care, tax administration and economic forecasting should be classified by risk and matched with proportionate audit, explainability and human-oversight protocols.

**Task-based AI skills mapping.** Reskilling should be organized around task groups (routine cognitive, standardized analytical, communicative, creative-strategic, high-context social) rather than around occupational titles, in line with the task-based labor-market framework (Acemoglu & Restrepo, 2019; Eloundou et al., 2024).

**SME AI-readiness program.** Without targeted support for small and medium enterprises in data governance, cloud services, cybersecurity and AI literacy, productivity gains will concentrate in large incumbents (Bessen, 2020). A national program combining infrastructure, training and advisory services is justified by the GII innovation-output gap documented in Section 5.

**Legal-ethical AI governance framework.** A risk-based regulatory framework covering high-risk AI registration, model audit, explainability, human oversight, bias testing, personal-data protection and contestation rights addresses the institutional gaps revealed by the GAIRI Governance pillar score (50.0) and is a precondition for citizen trust (NRI Trust score 38.10).

## 8. LIMITATIONS AND FUTURE RESEARCH

The study has five main limitations. First, STRI is a diagnostic readiness measure, not a causal econometric model; it does not estimate the marginal effect of AI on GDP, employment or productivity. Causal estimation would require sectoral microdata, time-series panels and quasi-experimental research designs.

Second, the peer-group sample (n = 7 including Azerbaijan) is small, which limits the statistical power of the concurrent-validity tests. Future iterations should expand the peer group to 15–25 upper-middle-income economies and add an EU comparator subgroup.
Third, the index relies on annual snapshots of international indicators. A dynamic panel covering 2020–2025 would allow assessment of national trajectories and identification of which components explain Azerbaijan's movement across digital-government, innovation and AI-readiness rankings.
Fourth, the model does not yet decompose AI readiness by sector (public administration, finance, education, health care, manufacturing, logistics). Sector-specific AI-readiness indicators are an important direction for future work.
Fifth, the inclusion dimension is approximated through NRI subcomponents. Future studies should add original citizen-survey data on trust, satisfaction, access and discrimination risk to give the inclusion dimension a stronger micro-foundation.

## 9. CONCLUSION

This paper developed and validated STRI, a composite diagnostic of AI-driven socioeconomic transformation readiness, and applied it to Azerbaijan benchmarked against six South-Caucasus and Central-Asian peers. The baseline STRI score for Azerbaijan is 55.96 with a 95% Monte Carlo interval of 52.4–59.1, placing the country in the medium-readiness band and below the peer-group mean of 63.16. Strengths concentrate in digital government; binding constraints lie in innovation outputs, social inclusion and AI governance.
STRI correlates positively and significantly with GDP per capita ($\rho = 0.71$) and ICT services exports ($\rho = 0.68$) across the peer group, supporting concurrent validity. The conceptual contribution is to integrate productivity, labor, inclusion, governance and accountability into a single transformation chain. The empirical contribution is the first peer-validated AI-readiness benchmark for the South-Caucasus region. The policy contribution is a phased implementation model and a national AI dashboard built on the same diagnostic logic.
Sustainable AI transformation depends less on technology deployment alone and more on the institutional capacity to ensure data quality, human oversight, ethical audit, legal accountability and public trust. STRI offers policymakers, regulators and researchers a transparent, replicable instrument to monitor those conditions and to align strategic intent with operational reality.

## DATA AVAILABILITY

All raw data are taken from publicly available sources: UN E-Government Knowledgebase (UN DESA, 2024), Network Readiness Index 2025 (Portulans Institute, 2025), Global Innovation Index 2025 (WIPO, 2025), Government AI Readiness Index 2025 (Oxford Insights, 2025), World Bank Open Data (2025) and WTO Trade in Services (2024). Processed datasets and calculation scripts are available from the author upon reasonable request.

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