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Table of Contents

Foreword

Dear Readers,

The modern global economy is transforming at an unprecedented pace. The rapid wave of digitalization, the integration of artificial intelligence, the transition toward a green and circular economy driven by climate change, and evolving patterns in global trade demand a comprehensive re-evaluation of traditional economic theories. At this historic juncture, we take great pride in presenting the inaugural issue of **"NeoEcon Review"**, a journal launched with the mission to provide scientific and practical answers to these emerging challenges.

The primary objective of our journal is to thoroughly investigate both the theoretical and practical aspects of modern economics, introduce innovative approaches, and contribute significantly to global academic discourse. We aim to establish a reliable and highly practical repository of knowledge for both scholars pursuing fundamental research and policy-makers executing strategic decisions.

To ensure seamless integration with the international academic community, the journal accepts and publishes articles exclusively in English. "NeoEcon Review" covers a broad and highly relevant spectrum of topics, ranging from the digital and platform economy to sustainable development, global financial markets to the creative and sharing economy, and institutional reforms to labor market dynamics.

We firmly believe that the insights and research presented here will serve as a vital beacon for understanding contemporary trends and shaping the economic policies of the future. We warmly invite all researchers who wish to be a part of this global scientific dialogue to contribute their innovative work to our journal.

Sincerely,
Doc.E.S., Prof. Shahin Sadigov
Chairman of the Board
of the Economic Scientific Research Institute
under the Ministry of Economy of the Republic of Azerbaijan

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 (ρ = 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 ($\rho = 0.74$); 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 (ρ = 0.71) and ICT services exports (ρ = 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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BEHAVIORAL ECONOMICS AND GREEN ENERGY ADOPTION: A REVIEW OF NUDGES, EXPERIMENTAL EVIDENCE, AND POLICY APPLICATIONS

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ABSTRACT

This study examines the role of behavioral nudges in fostering green energy adoption, emphasizing experimental evidence and policy implications. Drawing on theories such as Expected Utility Theory, Prospect Theory, and Nudge Theory, the paper explores how psychological and cognitive factors influence energy-related decision-making. Behavioral tendencies such as status quo bias, loss aversion, and social norm adherence are analyzed in their capacity to impede or enhance the adoption of renewable energy technologies. Empirical evidence highlights the efficacy of interventions like green defaults, feedback mechanisms, and competence-boosting strategies in promoting sustainable behaviors. Studies demonstrate significant energy savings through tailored nudges, with persistent effects when interventions account for socio-economic and cultural contexts. Ethical considerations, including transparency and autonomy, are also discussed. The review underscores the potential of combining behavioral insights with economic policies to overcome psychological barriers to green energy adoption. Future research should focus on the scalability of nudges, the integration of emerging technologies, and addressing inequalities to ensure equitable access to renewable energy solutions.

Keywords: behavioral nudges, green energy adoption, prospect theory, nudge theory, expected utility theory, energy policy, psychological barriers.

JEL Classification: D90, Q4, Q5.

1. INTRODUCTION

The global transition to green energy is essential to mitigate escalating climate challenges, meet rising energy demands, and reduce greenhouse gas emissions. Renewable energy sources, such as solar, wind, and hydropower, are pivotal in achieving these goals. However, despite advancements in renewable technologies and supportive policies, adoption rates remain insufficient to meet international climate targets (IRENA, 2024). This gap highlights the need for innovative strategies to complement traditional policy tools.

Behavioral economics offers a novel perspective for addressing the non-technological barriers to green energy adoption. By examining psychological and cognitive influences on decision-making, behavioral interventions—such as nudges—have demonstrated promise in encouraging pro-environmental behavior through cost-effective, non-coercive methods. Unlike traditional policies, which focus on economic incentives, nudges tackle biases like inertia and present bias, making them particularly relevant for fostering sustainable energy transitions (Allcott & Mullainathan, 2010; R. H. Thaler & Sunstein, 2008).

This study investigates the potential of behavioral nudges to accelerate green energy adoption by addressing the following key questions:

How do behavioral nudges, such as defaults and feedback mechanisms, influence consumer and investor decisions?

What role do psychological factors play in promoting or hindering renewable energy adoption?

How can behavioral insights be ethically integrated into policy frameworks to maximize impact?

The objectives of this research are to:

Synthesize empirical evidence on the effectiveness of behavioral nudges in green energy transitions.

Analyze the interplay between psychological factors and renewable energy decision-making.

Develop actionable policy recommendations to enhance the scalability and impact of nudge-based interventions.

By bridging the gap between economic models and behavioral insights, this study aims to provide a comprehensive framework for advancing the global transition to sustainable energy. It offers practical strategies for policymakers, energy providers, and researchers dedicated to promoting renewable energy adoption.

2. LITERATURE REVIEW AND THEORETICAL FRAMEWORK

This section integrates behavioral insights and traditional policy instruments to analyze decision-making processes related to green energy adoption. By synthesizing Expected Utility Theory (EUT), Prospect Theory, and Nudge Theory, it explores how cognitive biases and psychological tendencies influence the adoption of renewable energy technologies. The framework also examines actionable strategies to address these barriers through behavioral nudges.

2.1. Literature Review

2.1.1. Expected Utility Theory and Prospect Theory

Expected Utility Theory (EUT) posits that individuals make rational decisions by weighing the costs and benefits of available choices to maximize their utility (Neumann & Morgenstern, 1953). The Expected Utility Theory formula calculates the utility of outcomes as follows:

$$EU = \sum_{i=1}^{n} u(x_i)p_i$$

p_i indicates the probability of the outcome x_i and $u(x_i)$ indicates the benefit of obtaining the outcome x_i. Bernoulli observed that a certain amount of money is worth more to a poor person than to a rich person. Thus, as welfare increases, marginal utility decreases. This ensures that the utility function is concave (Trepel et al., 2005).

Shortly after the introduction of Expected Utility Theory (EUT) by Von Neumann and Morgenstern in 1944, its descriptive validity came under scrutiny. A significant challenge arose from the Allais Paradox, introduced by Maurice Allais in 1952, which demonstrated inconsistencies in the decision-making of prominent economists like Samuelson, Arrow, and Friedman. In the Allais paradox, the participant must select one option from a set of choices labeled A, B, C, and D.

First choice

(A): A profit of $1 million will definitely be made,

(B): 10% chance of winning $5 million, 89% chance of winning $1 million, 1% chance of winning nothing,

The second option

(C): 11% chance of winning $1 million, 89% chance of nothing,

(D): 10% chance of winning $5 million, 90% chance of nothing.

Allais anticipated that people would choose option A over option B. This was because in option A, becoming a millionaire was certain. However, based on the expected utility formula, option B should have been favored. Similarly, in another scenario, option C should have been chosen over option D, but people preferred option D over option C. This means that having a 10% chance of winning $5 million was seen as better than having an 11% chance of winning $1 million. Thus, this situation contradicts the assumptions of expected value theory and leads to a paradox (Aksoy T. and Şahin İ., 2015; Kahneman, 2011).

While EUT assumes rational decision-making, real-world choices often diverge due to psychological biases and incomplete information. For example, in renewable energy investments, traditional EUT models may fail to account for consumers' undervaluation of long-term savings and overemphasis on upfront costs. These shortcomings highlight the need for behavioral models that capture such complexities.

To address these inconsistencies, Kahneman and Tversky (1979) introduced Prospect Theory (PT), which demonstrates that individuals perceive gains and losses asymmetrically. Losses tend to loom larger than equivalent gains, a phenomenon known as loss aversion. PT suggests that individuals evaluate outcomes based on gains and losses relative to a reference point rather than final wealth. Its value function is concave for gains, convex for losses, and steeper for losses, reflecting **loss aversion**. Additionally, PT accounts for **diminishing sensitivity**, where changes near zero are perceived as more significant than those at higher magnitudes (Thaler, 1980).

The **Prospect Theory formula** evaluates the subjective value of outcomes as:

$$f = \sum_{i=1}^{n} \pi(p_i) \cdot v(x_i)$$

Here:

- $\pi(p_i)$ represents the weight assigned to probability (p_i) by the probability weighting function.
- $v(x_i)$ represents the value assigned to outcome x_i by the value function.

PT introduces a two-stage process: **editing** and **evaluation**. In the editing stage, individuals structure information through encoding, cancellation, and other operations. In the evaluation stage, prospects are assessed using subjective probabilities and values. Unlike EUT, PT incorporates framing effects, reference dependence, and psychological principles, offering a nuanced model for real-world decision-making (Kahneman & Tversky, 1979; Trepel et al., 2005).

This insight is particularly relevant in green energy adoption, where the upfront costs of renewable technologies, such as solar panels, often deter consumers despite the long-term benefits of energy savings and reduced environmental impact.

In addition to loss aversion, Prospect Theory's concept of probability weighting—where individuals overestimate small probabilities and underestimate large ones—has significant implications for green energy adoption. For instance, consumers may overestimate the risk of technology failure while underestimating the broader risks of climate inaction.

These findings underscore the importance of designing policies that minimize perceived losses while emphasizing future gains. For instance, framing renewable energy investments as long-term financial benefits rather than immediate expenses could help mitigate loss aversion and foster sustainable energy transitions.

While EUT assumes individuals make decisions by maximizing utility based on objective probabilities and outcomes, real-world behavior frequently diverges due to phenomena like loss aversion and probability weighting, as highlighted by Prospect Theory (Kahneman & Tversky, 1979).

2.2. Theoretical Framework

These insights set the stage for the application of Nudge Theory, which operationalizes these behavioral tendencies into practical interventions (Thaler and Sunstein, 2008). Nudges leverage biases such as inertia, framing effects, and social norms to influence decision-making without restricting individual freedom. For instance, setting renewable energy as the default option exploits the status quo bias (Samuelson and Zeckhauser, 1988), while feedback mechanisms address loss aversion by framing long-term benefits as immediate gains (Frederiks et al., 2015). Thus, Nudge Theory bridges the gap between theoretical models of human behavior and actionable strategies for fostering green energy adoption.

2.2.1. Nudge Theory and Psychological Barriers to Green Energy Adoption

Nudge Theory, popularized by Thaler and Sunstein (2008), provides a framework for influencing behavior through subtle changes in choice architecture. A nudge is defined as any intervention that steers individuals toward a specific decision while preserving freedom of choice and avoiding significant economic incentives. Nudges are particularly effective in addressing complex decisions with long-term trade-offs, such as adopting renewable energy technologies.

Advancements in technology have expanded the scope of nudging. Digital tools, such as personalized energy reports, real-time consumption feedback, and mobile apps, have enhanced the precision and scalability of behavioral interventions. However, these tools also raise ethical concerns about data privacy and consent.

Behavioral economics identifies several psychological barriers that hinder green energy adoption, including the following:

Status Quo Bias: Households often resist change, preferring familiar behaviors over greener alternatives, even when the latter offer substantial benefits (Frederiks et al., 2015; Samuelson and Zeckhauser, 1988). For example, setting renewable energy as the default option in utility plans significantly boosts adoption rates (Pichert and Katsikopoulos, 2008).

Loss Aversion and Framing Effects: The fear of losses outweighs potential gains, deterring investments in renewable technologies with high upfront costs (Kahneman and Tversky, 1979). Framing interventions, such as presenting the financial losses of inaction, have proven effective in countering this bias (Frederiks et al., 2015).

Social Norms and Peer Influence: Social comparisons strongly influence energy behaviors. Feedback mechanisms comparing household energy consumption to neighbors' averages have been shown to reduce energy use significantly (Allcott & Rogers, 2014; Frederiks et al., 2015; PW Schultz, 2014).

Temporal Discounting: Consumers often prioritize immediate costs over long-term benefits, a bias known as temporal discounting. Visualization tools that highlight future savings can make long-term benefits more salient, thereby encouraging investments in renewable technologies (Frederiks et al., 2015).

Trust and Credibility: Trust in energy providers and policymakers plays a pivotal role in renewable energy decisions. Transparent communication and endorsements from credible sources, such as local leaders or environmental organizations, enhance trust and adoption rates (Frederiks et al., 2015).

2.2.2. Strategies for Promoting Green Energy Adoption

Nudging strategies provide actionable solutions to address the psychological barriers outlined above. These strategies fall into four key categories:

Green Defaults: Setting renewable energy as the default option by utility providers has been highly effective in guiding behavior. Studies show that individuals are more likely to stick with default options, as seen in Germany, where over 99% of households maintained green energy use when it was the default setting (Schubert, 2017).

Social Incentives: Leveraging social norms through peer comparisons and public recognition fosters pro-environmental behavior. For instance, providing households with monthly energy reports comparing their usage to neighbors' averages has significantly reduced energy consumption (Allcott & Rogers, 2014).

Feedback Mechanisms: Real-time feedback on energy consumption, such as via smart meters or eco-labeling, enhances awareness and promotes sustainable decisions. Comparative data on energy performance relative to peers drives energy-saving behaviors (Sörqvist & Langeborg, 2019).

Reducing Barriers to Action: Simplifying processes, such as solar panel installation, or providing financial incentives like subsidies, reduces friction and improves adoption rates (Cosic et al., 2018).

The effectiveness of nudges also depends on how they are framed and the perceived effort required to comply. Grelle et al. (2024) found that nudges framed in a personal context ("you") are more impactful than those framed societally ("they"). Similarly, low-effort nudges are more widely accepted and effective, underscoring the need for simplicity in design (de Groot & Schuitema, 2012; Hagmann et al., 2019; Rodriguez-Sanchez et al., 2018).

Cultural Context: Understanding the cultural context in which behavioral nudges are implemented is crucial for their effectiveness in promoting green energy adoption. Cultural norms, values, and socio-economic factors significantly influence individuals' perceptions and responses to nudges, necessitating a tailored approach to intervention design. For instance, research has shown that social norms play a pivotal role in shaping sustainable energy behaviors, with descriptive and injunctive norms varying widely across different cultural settings (Allcott, 2011). In regions where community-oriented values prevail, nudges that leverage social comparisons may be particularly effective, as individuals are motivated by the desire to conform to group behaviors. Conversely, in cultures that emphasize individualism, personal choice and autonomy may take precedence, suggesting that nudges should be framed to highlight personal benefits and control (Schubert, 2017). Furthermore, socio-economic factors, such as income levels and access to renewable technologies, can affect the receptiveness to nudges and the feasibility of adopting green energy solutions (Andor et al., 2020; Brick et al., 2023). Therefore, this study will incorporate a culturally sensitive approach, adapting nudging strategies to align with the specific values, beliefs, and circumstances of the target populations. By doing so, the research aims to enhance the relevance and impact of behavioral interventions in diverse cultural contexts, ultimately contributing to more effective strategies for fostering sustainable energy practices.

3. METHODOLOGY

This study employs a qualitative and quantitative approach to examine the effectiveness of behavioral nudges in promoting green energy adoption. The research synthesizes existing empirical evidence from experimental studies, field trials, and policy interventions, drawing on data from a range of socio-economic and cultural contexts. The methodology is structured around two primary components: a review of theoretical frameworks and an analysis of empirical studies.

The study follows a structured narrative review approach with elements of systematic review. The literature is selected based on relevance to behavioral economics, green energy adoption, and policy applications. The main sources include peer-reviewed journal articles, reports, and experimental studies published mostly in the last two decades, with more focus on recent studies. The selection criteria include: (1) direct relation to behavioral nudges or energy behavior, (2) empirical or experimental evidence, and (3) policy relevance. The analysis is based on comparative and thematic synthesis, where findings from different studies are grouped and compared to identify common patterns, differences, and key insights.

Guided by the behavioral insights and theoretical constructs presented in the preceding section, this study focuses on empirical evidence and experimental interventions to evaluate the effectiveness of nudges in promoting green energy adoption.

Empirical Evidence Review: A systematic review of existing literature is conducted, focusing on experimental and policy-based interventions that utilize behavioral nudges to promote renewable energy adoption. The review includes both large-scale randomized controlled trials (RCTs) and smaller-scale field experiments that measure the impact of nudges such as green defaults, feedback mechanisms, and social norm interventions. The selected studies are analyzed in terms of their design, sample size, methodologies, and findings. Key studies provide empirical insights into the effectiveness of nudges in varying contexts.

Data Analysis: Quantitative data from these empirical studies are analyzed to assess the impact of specific nudging strategies on green energy adoption rates. This includes evaluating adoption rates, energy consumption reductions, and the persistence of behavioral changes over time. Additionally, qualitative insights from case studies and interviews are synthesized to gain a deeper understanding of consumer perceptions, motivations, and barriers to adopting green energy solutions. These qualitative findings complement the quantitative data, offering a holistic view of nudge effectiveness.

Through this methodology, the study aims to provide a comprehensive analysis of how behavioral nudges can be leveraged to facilitate green energy adoption while addressing the psychological and cognitive barriers that hinder pro-environmental behavior.

4. EMPIRICAL EVIDENCE FROM EXPERIMENTAL STUDIES

The following section examines key empirical evidence from experimental studies on the determinants, barriers, and behavioral interventions that shape green energy adoption. By exploring the influence of psychological and economic factors, as well as the role of behavioral interventions like nudges and boosts, this section provides a comprehensive understanding of how individuals make decisions regarding sustainable energy. It also delves into the impact of social norms and contextual tailoring of nudges in driving green energy behaviors across diverse socio-economic and cultural settings. Together, these studies offer valuable insights into designing effective interventions for enhancing green energy adoption, making it a more sustainable and long-term practice. The subsequent sections present these findings, focusing on the barriers to adoption, the effectiveness of behavioral strategies, and the role of contextual adaptations.

4.1. Methodological Insights from Empirical Studies

To provide greater clarity and context to the empirical findings discussed in this paper, it is essential to examine the methodologies employed in the cited studies. This section outlines the methods used to gather evidence on the effectiveness of behavioral nudges for green energy adoption and discusses potential biases and limitations that may influence the interpretation of results.

Study Designs and Data Collection Methods: The majority of studies cited in this paper utilized randomized controlled trials (RCTs), surveys, and field experiments to evaluate the impact of behavioral nudges. For instance:

- Paunov and Grüne-Yanoff (2023) conducted a 29-week RCT in a student dormitory to compare the effectiveness of nudges and boosts in reducing energy consumption. The trial involved goal-setting, commitment, and feedback interventions for one group, while another group received competence-enhancing tips tailored to household devices.
- Anagnostopoulos (2024) employed large-scale field experiments to test digital nudges, such as smart meters and mobile apps, across multiple European countries. These studies relied on energy usage data collected in real-time to quantify reductions in consumption.

Sample Sizes and Representation: The robustness of findings often depends on the sample size and demographic diversity of participants. For example:

- Allcott (2011) evaluated Home Energy Reports (HERs) using a large sample of U.S. households, which enhanced the generalizability of results. However, smaller-scale studies, such as those conducted by Cosic et al., (2018) on recycling behavior in student settings, may have limited applicability to broader populations.

Temporal Scope of Studies: Many studies focus on short-term interventions, which limits insights into the long-term sustainability of behavioral nudges. For instance, while Paunov and Grüne-Yanoff (2023) demonstrated the initial success of nudges, their effectiveness waned over time, highlighting the need for follow-up research to assess the persistence of behavioral changes.

Potential Biases and Limitations:

- Sample Bias: Some studies relied on self-selected participants, which may introduce bias. For example, participants in energy-saving trials might already possess pro-environmental attitudes, skewing the results.
- Contextual Variability: Regional differences in socio-economic and cultural factors can influence the effectiveness of nudges. For instance, Anagnostopoulos (2024) reported higher adoption rates in high-income households, suggesting income disparities play a role in intervention success.
- Measurement Constraints: Studies employing self-reported data may face accuracy issues due to recall bias or social desirability bias. Complementing self-reports with objective measures (e.g., energy consumption logs) can improve reliability.

By synthesizing these methodological insights, this section underscores the importance of contextualizing empirical findings within the framework of study designs, sample characteristics, and potential biases. These factors not only affect the validity and generalizability of results but also offer guidance for designing future research that addresses these limitations.

4.2. Determinants and Barriers to Green Energy Adoption

In light of the psychological and economic factors that influence green energy adoption, empirical data provides valuable insights into the drivers and barriers to this process. Zeng et al. (2022) examine these determinants and highlight several key factors that significantly affect consumers' decisions to adopt renewable energy technologies. Green Energy Technology Awareness (GETA) and Environmental Concern (EC) emerge as strong positive influencers, with significant β-values of +0.362 ($p < 0.05$) and +0.245 ($p < 0.1$), respectively. These findings underscore the importance of raising awareness and fostering environmental concern as effective strategies for promoting green energy uptake, particularly through targeted educational campaigns and normative messaging.

In contrast, Green Energy Technology Costs (GETCs) and Discomfort (GETD) are identified as critical barriers, with negative impacts of -0.325 ($p < 0.05$) and -0.395 ($p < 0.05$), respectively. These results suggest that perceived high upfront costs and discomfort with new technologies discourage consumers from transitioning to green energy solutions. Strategies such as subsidies to alleviate financial burdens and user-friendly designs to reduce discomfort could address these challenges effectively (Zeng et al., 2022).

Additionally, Openness to Experience (OE) positively influences adoption ($\beta = +0.256$, $p < 0.1$), indicating the potential of interventions tailored to individuals more receptive to adopting innovative technologies. Personalized nudges, such as highlighting the compatibility of green energy with modern lifestyles, could enhance adoption rates among this group.

These statistical insights provide a strong foundation for designing behavioral interventions aimed at mitigating barriers and amplifying motivators for green energy adoption. Table 1 summarizes key determinants of adoption, based on empirical research, and offers statistical insights into how awareness, costs, discomfort, and other factors shape consumer behavior (Zeng et al., 2022).

Table 1.

Key Factors Influencing Green Energy Adoption and Their Statistical Impact

Factor	Description	Impact on Adoption (β-value)	Statistical Significance
Green Energy Technology Awareness (GETA)	Knowledge and understanding of green technologies	0.362	p < 0.05
Green Energy Technology Costs (GETCs)	Perceived high upfront costs of renewable technologies	-0.325	p < 0.05
Environmental Concern (EC)	Consumers' attitudes toward environmental protection and climate issues	0.245	p < 0.1
Green Energy Technology Discomfort (GETD)	Perceived difficulty in using or understanding renewable technologies	-0.395	p < 0.05
Openness to Experience (OE)	Willingness to explore and adopt new technologies	0.256	p < 0.1

Source: *Zeng et al., 2022.*

4.3. Behavioral Interventions for Sustainable Practices: Nudges, Boosts, and Their Long-Term Effects

Behavioral interventions such as nudges and boosts offer unique approaches to fostering sustainable practices, with varying degrees of effectiveness in different contexts. Paunov and Grüne-Yanoff (2023) explored these methods in a long-term randomized controlled trial conducted in a student dormitory. Their study compared the effects of nudges—behavioral strategies involving goal-setting, commitment, feedback, and social comparison (Abrahamse et al., 2005; Karlin et al., 2015) - against boosts, which focused on enhancing individuals' competence through automated bi-weekly energy-saving tips tailored to household devices (Hertwig and Grüne-Yanoff, 2017).

The findings revealed that boosts significantly outperformed nudges in reducing energy consumption over the 29-week period, with participants in the boosting group consuming approximately 3 MWh less electricity than those in the nudging group. While nudging showed initial success, its effects waned over time. In contrast, boosts maintained their impact, suggesting that interventions aimed at improving knowledge and skills lead to more enduring behavioral changes. These results emphasize the importance of competence-based approaches for long-term energy conservation and underscore the need for policymakers to integrate these strategies into sustainable energy initiatives.

Anagnostopoulos (2024) evaluates behavioral interventions in promoting energy-saving and green energy adoption through case studies across Europe. Key findings show that digital nudges, like smart meters and mobile apps, reduced energy consumption by 5–12%, with higher savings for more engaged households. Social norm-based interventions, providing feedback on neighbors' energy-saving behaviors, led to savings of up to 15%, especially among high-consumption households. Additionally, setting renewable energy as the default option resulted in adoption rates exceeding 90%, illustrating the impact of cognitive biases such as inertia. The report also highlights the importance of tailoring interventions to socio-economic contexts, showing that combining financial incentives with behavioral nudges moderately improved adoption in low-income households. These results suggest that tailored behavioral interventions can significantly influence energy behaviors, offering cost-effective solutions for advancing green energy transitions (Anagnostopoulos, 2024).

A summary of the experimental results is presented in the Table 2 below:

Table 2.

Summary of Behavioral Interventions and Their Impact on Green Energy Adoption

Intervention	Impact	Additional Insights
Digital Nudges (Smart Meters and Apps)	Energy consumption reduced by 5–12%	Higher engagement with real-time feedback resulted in greater savings.
Social Norm Comparisons	Energy savings up to 15% in high-consumption households	Peer feedback significantly influenced behavioral adjustments; descriptive norms played a key role.
Green Defaults	Adoption rates exceeding 90%	Setting renewable energy as the default option minimized cognitive barriers, such as inertia and status quo bias.
Low-Income Targeted Nudges	Moderate adoption improvement with financial incentives	Combined behavioral and financial strategies proved effective in addressing economic constraints.

***Source:** Anagnostopoulos, 2024.*

These findings underscore the potential of behavioral nudges to complement traditional energy policies. They also highlight the role of innovative, scalable solutions such as digital platforms in driving the global transition to sustainable energy systems. Further research is recommended to assess the long-term impacts of these interventions and their applicability beyond the European context (Anagnostopoulos, 2024).

Complementing this, the study by Cosic et al. (2018) investigated the impact of nudges on students' ecological behaviors, focusing on recycling practices. Conducted at the Scuola Superiore Sant'Anna in Pisa, this field experiment employed a combination of nudges, including social norm and "easy-to-do" nudges, over a 60-day intervention period. These interventions significantly improved recycling rates for plastic cups, leveraging social norms to influence individual actions. Previous literature (Cialdini et al., 1990; Goldstein et al., 2008) supports the idea that social norms motivate behavior through perceived social penalties for non-compliance and assumptions about others' superior knowledge.

Notably, the nudges' effects persisted three months after the intervention, highlighting their potential for creating lasting behavioral change. This aligns with findings from Paunov and Grüne-Yanoff (2023), suggesting that combining short-term motivators like nudges with competence-building boosts could enhance the longevity and efficacy of sustainable interventions.

Both studies offer valuable insights for policymakers and environmental advocates. While nudges are effective in addressing immediate behavioral barriers, boosts provide the tools necessary for sustained changes in energy conservation and waste management practices. Together, these approaches can form the foundation for comprehensive strategies aimed at promoting green energy adoption and ecological responsibility in various settings.

While quantitative evidence provides valuable insights into the statistical effectiveness of behavioral nudges (Anagnostopoulos, 2024; Paunov & Grüne-Yanoff, 2023), incorporating qualitative perspectives can offer a deeper understanding of individual and community experiences with these interventions (Frederiks et al., 2015). For instance, qualitative data from interviews, focus groups, or case studies can reveal how consumers perceive and respond to nudges, shedding light on emotional, cultural, and contextual factors that influence behavior (Allcott, 2011). Understanding why certain households resist default green energy options despite clear economic benefits could inform the design of more culturally sensitive and user-centered interventions (Schubert, 2017). Balancing quantitative metrics with qualitative narratives ensures a more comprehensive evaluation of nudge effectiveness, enabling policymakers to design interventions that are both empirically robust and socially resonant (Thaler and Sunstein, 2021).

Social Norms and Contextual Tailoring in Behavioral Nudges for Green Energy Adoption: Behavioral nudges leveraging social norms and contextual adaptations have demonstrated their potential to encourage green energy adoption, but their effectiveness varies based on regional, cultural, and socio-economic factors. Studies from the United States, Germany, and South Africa highlight critical lessons in applying these interventions to promote energy conservation and sustainability goals.

The Role of Social Norms in Green Energy Adoption

Social norms, both descriptive and injunctive, have been pivotal in shaping sustainable energy behaviors. For example, Allcott's (2011) large-scale randomized controlled trial in the United States evaluated Home Energy Reports (HERs) that provided households with feedback comparing their electricity use to similar households. By leveraging descriptive norms (average neighborhood consumption) and injunctive norms (smiley emoticons to reinforce approval or disapproval), HERs reduced electricity consumption by an average of 1.9–2.0%. Notably, high-energy consumers achieved the largest reductions, while injunctive norms mitigated the boomerang effect among low-energy households.

These interventions proved cost-effective, with an estimated cost of $0.03 per kilowatt-hour saved, significantly less than traditional subsidies for energy-efficient appliances. The persistence of savings over time further underscores the habit-forming potential of periodic feedback, making social norm nudges a scalable and economical tool for fostering energy-efficient behaviors. Extending these insights to green energy adoption, descriptive norms, such as feedback on neighborhood participation in renewable energy programs, and real-time feedback on energy savings from solar panels, could enhance the uptake of green technologies (Allcott, 2011).

Contextual Tailoring: Insights from Germany and South Africa

The contextual effectiveness of behavioral nudges is evident in comparative studies from Germany and South Africa. In Germany, Andor et al. (2020) applied HERs to 11,630 households, yielding a modest 0.7% reduction in electricity consumption—significantly lower than U.S. results. This disparity was attributed to Germany's lower baseline electricity consumption and less energy-intensive practices. However, high-energy households in Germany achieved reductions of up to 3.1%, showcasing the importance of targeted interventions. Despite these successes, the cost of CO2 abatement was significantly higher in Germany ($505 per ton) than in the U.S., raising questions about cost-effectiveness.

In contrast, South Africa's experience during Cape Town's severe drought (2015–2018) highlights the influence of socio-economic disparities on nudge effectiveness. Brick et al. (2023) evaluated interventions, including social recognition, public good messaging, and financial feedback, to reduce water consumption. High-income households achieved savings of up to 2.3% through social recognition, while middle-income households responded better to financial feedback. However, structural barriers, such as inadequate infrastructure, limited the responsiveness of low-income households.

To better understand the effectiveness of behavioral nudges for green energy adoption across different regions, the following table summarizes key data from studies conducted in the United States, Germany, and South Africa (Table 3):

Table 3.

Effectiveness and Cost-Effectiveness of Behavioral Nudges for Green Energy Adoption Across Different Regions

Study	Location	Sample Size	Intervention	Effectiveness	Cost-Effectiveness	Key Insights
(Allcott, 2011)	United States	Large-scale trial	Home Energy Reports (HERs)	Reduced electricity consumption by 1.9–2.0%	$0.03 per kWh saved	High-energy consumers showed largest reductions, and injunctive norms mitigated the

						boomerang effect among low-energy households.
(Andor et al., 2020)	Germany	11,630 households	Home Energy Reports (HERs)	0.7% reduction in electricity consumption (average)	$505 per ton CO2 abated	Lower baseline electricity consumption and less energy-intensive practices led to lower effectiveness compared to the U.S., but high-energy households showed up to 3.1% reduction.
(Brick et al., 2023)	South Africa (Cape Town)		Social recognition, public good messaging, financial feedback	High-income households: 2.3% savings		Socio-economic disparities influenced effectiveness; high-income households responded better to social recognition, while middle-income responded to financial feedback.

Source: *Compiled by the author.*

Based on the results presented above, a comparative view shows that the effectiveness of behavioral nudges varies significantly across regions. For example, energy savings in the United States are higher than in Germany, which can be explained by differences in baseline energy consumption and behavioral patterns. In both cases, high-energy users respond more strongly to interventions compared to low-energy users.

In addition, the results from South Africa show that socio-economic factors play an important role. High-income households respond better to social recognition, while middle-income households react more to financial feedback. This suggests that the same type of intervention may produce different results depending on income level and local conditions.

Overall, these findings indicate that behavioral nudges are context-dependent and should be carefully adapted to regional and socio-economic characteristics to achieve better outcomes.

Green Nudges: Applications for Green Energy Adoption: Schubert (2017) examines the effectiveness and ethical implications of green nudges—behavioral interventions designed to encourage environmentally responsible behaviors, such as adopting renewable energy or reducing resource consumption. The study highlights several examples of successful green nudges, emphasizing their context-dependent nature. For instance, in Schönau, Germany, a change in the default setting to renewable energy resulted in over 99% of households maintaining green energy use, compared to the national average of only 1% (Schubert, 2017). Similarly, in large-scale field experiments involving 600,000 U.S. households, Opower's Home Energy Reports, which compared energy consumption to that of neighbors, reduced energy use by 1.4–3.3%, illustrating the potential of peer comparison and social norms in influencing sustainable behaviors. The study also discusses the impact of descriptive norms on behaviors like hotel towel reuse, which increased by 9–10% when guests were informed about the reuse practices of their peers (Table 4).

Table 4.

Statistical summary of the study

Intervention	Location	Outcome
Default Setting	Schönau, Germany	99% adoption of renewable energy vs. 1% nationally.
Home Energy Reports (HERs)	600,000 U.S. households	Energy consumption reduced by 1.4–3.3%.
Hotel Towel Reuse	Various locations	Towel reuse increased by 9–10% with social norms.
Behavioral Framing	Denmark, Smart Grid adoption	Increased awareness and adoption of renewables.

Source: *Schubert, 2017.*

However, Schubert (2017) critically addresses the ethical dimensions of nudges, particularly concerns related to autonomy and manipulation. Nudges, while effective, may undermine individual autonomy by shaping choices in ways that individuals may not consciously endorse, raising ethical questions about their transparency and the potential for coercion. This ethical framework offers valuable insights for the design of behavioral policies, ensuring they balance effectiveness with respect for personal freedoms and autonomy.

While these studies demonstrate the effectiveness of behavioral interventions, several gaps remain. For instance, there is limited evidence on the long-term sustainability of nudges and their impact in developing regions. Additionally, cultural and socio-economic factors may influence the effectiveness of interventions, necessitating further contextual research.

In addition to the limitations discussed above, there are also broader critical perspectives on the use of nudges:

First, "nudge backlash" can occur when individuals feel that their choices are being manipulated. This can reduce trust in policymakers and decrease the effectiveness of interventions.

Second, rebound effects may reduce the overall impact of energy-saving behaviors. For example, individuals who save energy in one area may increase consumption in another area, which offsets the initial benefits.

Third, there is political and ethical criticism of nudging. Some researchers argue that nudges can be used as a tool of soft control, especially in neoliberal policy frameworks, where responsibility is shifted from institutions to individuals. In this case, structural problems may not be fully addressed.

Moreover, empirical evidence on unsuccessful or weak nudges is limited, as many studies focus mainly on positive results. This creates a potential bias in the literature. Therefore, future research should pay more attention to negative results, long-term limitations, and differences across contexts.

These critical perspectives show that nudges should not be seen as a complete solution. Instead, they should be combined with traditional policies, such as regulation and financial incentives, to achieve more effective and balanced outcomes.

5. POLICY IMPLICATIONS AND RECOMMENDATIONS FOR GREEN ENERGY ADOPTION USING BEHAVIORAL NUDGES

The transition to green energy is critical for addressing climate change, but adoption rates of renewable technologies remain insufficient to meet global climate targets. Despite technological advancements and supportive policies, non-technological barriers, such as psychological biases, inertia, and social norms, hinder widespread adoption. This study highlights the potential of behavioral nudges—subtle interventions that alter choice architecture without restricting freedom of choice—as an effective policy tool for overcoming these barriers. Below are key policy implications and recommendations based on the empirical findings and theoretical insights from this research.

5.1. Design Policies that Use Green Defaults to Maximize Renewable Energy Adoption

Empirical studies consistently show that green defaults—where renewable energy is automatically set as the default option—significantly increase adoption rates. Research from Germany (Schubert, 2017) demonstrated that over 99% of households remained in a green energy program when it was the default, compared to just 1% when participation required active choice. This aligns with the findings of Prospect Theory, which suggests that individuals are more likely to accept default options due to cognitive biases like inertia and loss aversion.

Governments should require green energy defaults in utility contracts and energy programs. This could be implemented by setting renewable energy as the default option for all consumers, with the freedom to opt-out if desired. This strategy can be particularly impactful in regions with low renewable energy adoption and can encourage large-scale transitions to sustainable energy sources.

5.2. Incorporate Social Norms and Peer Comparisons into Policy Frameworks

The role of social norms in shaping behavior is a powerful lever for encouraging green energy adoption. Studies, such as Allcott's (2011) on Home Energy Reports (HERs), demonstrate that feedback comparing household energy consumption to neighbors' averages effectively reduces consumption. Descriptive norms, which provide information about what others are doing, can be particularly influential when combined with injunctive norms that convey approval or disapproval of behaviors.

Policymakers should integrate social norm-based nudges into energy consumption programs. This can include providing households with comparative feedback on their energy usage relative to their neighbors, which has proven effective in reducing energy consumption. Additionally, using real-time feedback on the adoption of renewable energy technologies (e.g., participation rates in renewable energy programs) can drive individuals to align their actions with community behaviors, increasing overall adoption rates.

5.3. Leverage Real-Time Feedback to Combat Temporal Discounting

The psychological phenomenon of temporal discounting, where individuals prioritize immediate costs over long-term benefits, presents a significant barrier to the adoption of green technologies. Feedback mechanisms, particularly through smart meters and mobile apps, have been shown to reduce this bias by providing consumers with real-time data on their energy consumption and the long-term savings of renewable energy options (Sörqvist and Langeborg, 2019).

Governments and utilities should incentivize the use of smart meters and mobile apps that offer real-time feedback on energy consumption. These tools should include features that visualize potential long-term savings from renewable energy adoption, making future benefits more salient and reducing the bias toward immediate costs. Additionally, policies should encourage energy providers to integrate these tools into their service offerings, ensuring that they are accessible and widely used.

Address Financial Barriers with Targeted Financial Incentives: One of the strongest barriers to green energy adoption is the high upfront costs of renewable technologies, such as solar panels. As shown in the empirical studies by Zeng et al. (2022), the costs of green energy technologies are a major deterrent for many consumers, outweighing the perceived long-term savings. Loss aversion, as articulated in Prospect Theory, makes consumers more sensitive to immediate costs than to long-term benefits, further exacerbating this issue.

To address the financial barrier, policymakers should offer targeted financial incentives, such as subsidies, low-interest loans, or tax credits for renewable energy technologies, particularly for low- and middle-income households. These incentives can be paired with nudges that emphasize the long-term savings and environmental benefits, making the value proposition of green energy technologies more appealing and tangible.

Tailor Nudging Strategies to Regional and Socio-Economic Contexts: The effectiveness of behavioral nudges is not universal and varies based on regional, socio-economic, and cultural contexts. For example, studies in Germany and South Africa have demonstrated that the success of feedback-based interventions can depend on factors such as energy consumption habits and income levels (Andor et al., 2020; Brick et al., 2023). Tailoring interventions to address these contextual factors is essential for ensuring their effectiveness.

Tailor nudging strategies to specific regional and socio-economic contexts. For example, interventions in areas with higher energy consumption should focus on high-energy users, while in low-income areas, financial incentives and educational campaigns may be more effective. Policymakers should invest in segmentation strategies that account for demographic and behavioral differences among target populations to enhance the impact of nudges.

Ensure Ethical Transparency in the Design and Implementation of Nudges: The effectiveness of nudges raises important ethical considerations. As noted by Schubert, (2017), while nudges can drive behavior change, they may also manipulate individuals into choices

they do not fully endorse, potentially undermining autonomy. The lack of transparency in nudging practices can lead to ethical concerns, especially when personal data is involved.
Ensure ethical transparency in the design and implementation of nudges by clearly informing consumers about the intent and operation of nudging interventions. Publicly disclose how data is used and ensure that individuals have control over their participation in nudge-based programs. Ethical considerations should be central to policy development, ensuring that interventions respect individual autonomy while promoting collective environmental goals.
The ethical implications of using nudges to promote green energy adoption require careful consideration, particularly regarding individual autonomy and transparency (Schubert, 2017). While nudges are designed to subtly steer behavior without restricting freedom of choice, they may inadvertently manipulate individuals into decisions they might not consciously endorse (Thaler and Sunstein, 2021). For instance, setting renewable energy as the default option exploits status quo bias (Samuelson and Zeckhauser, 1988) but may fail to account for individual preferences or fully inform consumers about their choices. To address these concerns, policymakers must prioritize ethical transparency in the design and implementation of nudges. This includes clearly communicating the purpose of the intervention, ensuring that individuals can easily opt out, and safeguarding data privacy, especially when leveraging digital tools like smart meters or mobile apps (Frederiks et al., 2015). Balancing the effectiveness of behavioral nudges with respect for autonomy and informed consent is essential to ensure that these interventions remain both impactful and ethically sound.

CONCLUSION AND FUTURE RESEARCH DIRECTIONS

The findings of this review reveal that behavioral nudges, when effectively designed, can significantly influence green energy adoption. Green defaults, social norms, feedback, and competence-enhancing interventions have demonstrated measurable success in driving pro-environmental behaviors. These interventions leverage cognitive biases to create low-cost, scalable solutions for accelerating the transition to renewable energy.
However, the effectiveness of nudges is context-dependent, requiring careful consideration of socio-economic, cultural, and behavioral differences. Ethical concerns such as the potential for manipulation and the need to preserve individual autonomy must be addressed in policy design.
Future research should explore the integration of behavioral nudges with advanced technologies such as smart meters, AI-driven feedback systems for energy tracking. Longitudinal studies are needed to evaluate the durability of nudge effects over time. Additionally, there is a critical need to investigate how nudges can address energy inequalities, ensuring that interventions are inclusive and accessible to diverse populations.
By advancing these research directions, behavioral nudges can serve as a cornerstone for sustainable energy policies, fostering widespread adoption of renewable energy technologies.

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STRUCTURAL BARRIERS TO LABOR MARKET REINTEGRATION AND HUMAN CAPITAL RECOVERY IN POST-CONFLICT KARABAKH AND EAST ZANGEZUR

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ABSTRACT
Following the 2020 conflict, large-scale reconstruction and resettlement initiatives in Karabakh and East Zangezur have made labor market reintegration a central condition for sustainable economic stabilization. This article examines the mismatch between the employment potential of returning populations and the emerging regional economic structure, assessing its implications for long-term development. The analytical framework is grounded in Human Capital Theory, institutional economics and post-conflict recovery models. Methodologically, the study relies on the analysis of official statistical data and the evaluation of state employment and reconstruction programs. The findings indicate that infrastructure-led investments predominantly generate temporary employment, while the transition toward sustainable and productivity-enhancing jobs in manufacturing and services remains constrained by structural and institutional barriers. The discrepancy between the skill composition of the returning workforce and regional economic priorities weakens the labor market's capacity to integrate labor supply effectively. The article proposes a strategic approach to human capital recovery within the frameworks of green economy and smart village development, emphasizing the necessity of coordinated institutional reforms to ensure durable socio-economic reintegration.
Keywords: labor market reintegration, human capital, post-conflict economy, economic restructuring, regional development
JEL Classifications: J21, J24, J64, O33.

1. INTRODUCTION

Following 2020, Azerbaijan's economic system transitioned into a new phase of macroeconomic reality. The reintegration of the liberated Karabakh and East Zangezur1 territories into the national economy transcends mere physical infrastructure restoration and capital expenditure expansion. This process necessitates a fundamental restructuring of the institutional architecture2 and the functional integration of regional labor markets (Kərimov, 2025). The potential contribution of these territories to the national Gross Domestic Product is conditioned not only by the exploitation of natural resources and agrarian opportunities but also by effective labor division, productivity enhancement and the active inclusion of human capital into economic cycles. Amidst global digitalization trends and the technological paradigm shifts triggered by the Fourth Industrial Revolution, the competitive development of these regions requires precise institutional coordination and structural alignment of the labor market.

The phased demographic transition planned under the "Great Return" program highlights the labor market's absorptive capacity3 as a primary economic challenge. A significant structural mismatch4 exists between the occupational profiles and employment habits of formerly displaced persons who have functioned within urban environments for decades and the skill sets necessitated by the agro-industrial and "green economy" models currently being established in the liberated territories (Decree No. 2620 of the President of the Republic of Azerbaijan on measures to establish a "green energy" zone in the liberated territories of the Republic of Azerbaijan, 2021). This discrepancy creates an asymmetry between the qualitative parameters of labor supply and demand, thereby weakening the efficiency of allocation mechanisms within regional labor markets. Absent institutional regulation, state investments risk being confined to transitory employment effects.

The phenomenon of human capital depreciation in post-conflict zones remains a focal point of discussion in economic literature. Educational disruptions, skill obsolescence and labor market detachment during conflict periods diminish the valuation of human capital. Its recovery relies on targeted special economic zones, fiscal incentives, specialized training programs and innovation subsidies. These instruments must serve to accelerate not only the influx of capital but also the structural transformation of the labor market.

Existing scholarship has predominantly focused on the social and political dimensions of reintegration, leaving a void in comprehensive economic and institutional analysis. Specifically, there is a lack of systemic evaluation regarding the structural barriers to labor market reintegration, skill mismatches and the empirical efficacy of state programs. This article

[1] East Zangazur refers to the administrative and economic region established in the post-conflict period and formalised by the decree of the President of Azerbaijan on 7 July 2021, "On the new division of economic regions of the Republic of Azerbaijan."

[2] The formal and informal rules, regulations and organizational structures that govern economic behavior and policy implementation.

[3] The ability of a regional economy to integrate and utilize arriving labor resources and capital investments effectively.

[4] A situation in the labor market where the skills and locations of job seekers do not align with the requirements and locations of available vacancies.

aims to address this research gap by analyzing labor market barriers within an economic framework and providing strategic policy recommendations.

2. LITERATURE REVIEW

The academic literature on post-conflict economic recovery increasingly emphasizes the centrality of labor market reintegration and human capital restoration as key determinants of sustainable development. Early contributions, grounded in the human capital framework of Gary Becker, conceptualize skills, education, and experience as productive assets that depreciate under prolonged displacement. In post-conflict regions, this depreciation is often intensified by labor market detachment and occupational discontinuity, leading to persistent productivity gaps and structural unemployment.

Recent empirical studies extend this framework by examining the dynamics of labor markets in fragile and conflict-affected settings. Reports by the World Bank highlight that job creation in post-conflict regions is initially driven by public investment, particularly in infrastructure, but these employment effects are typically short-lived unless complemented by private sector development and sectoral diversification. The International Labour Organization underscores that skills mismatch remains a critical barrier to effective labor market reintegration, as returning populations often possess competencies misaligned with emerging economic structures.

A growing strand of literature focuses on structural transformation and sectoral shifts in post-conflict economies. According to Dani Rodrik, sustainable economic growth requires the reallocation of labor from low-productivity sectors to higher value-added activities, a process that is often constrained by institutional inefficiencies and coordination failures. In this context, labor market outcomes depend not only on the availability of jobs but also on the compatibility between workforce skills and sectoral demand. This is further reinforced by studies on skill mismatch, which demonstrate that both horizontal and vertical mismatches reduce labor productivity and hinder efficient resource allocation.

Institutional factors also play a decisive role in shaping labor market performance. The institutional economics approach, associated with Douglass North, argues that formal and informal rules govern economic interactions and determine the efficiency of resource allocation. Weak contract enforcement, information asymmetry, and underdeveloped labor market institutions can significantly reduce absorptive capacity, limiting the ability of regional economies to integrate returning populations effectively. Empirical evidence suggests that improving institutional quality, through transparent governance, efficient labor market intermediation, and active labor market policies, enhances both employment outcomes and productivity levels.

In parallel, the literature highlights the role of state intervention in facilitating labor market adjustment. The OECD emphasizes that well-designed active labor market policies, including vocational training, wage subsidies, and employment incentives, can mitigate the adverse effects of structural mismatch and accelerate workforce integration. The effectiveness of such policies depends on their alignment with market needs and their capacity to stimulate private sector participation, rather than creating dependency on public expenditure.

Attention has shifted toward the integration of "green" and "smart" development models in post-conflict recovery strategies. Studies indicate that the transition to a low-carbon economy and the adoption of digital technologies create new forms of labor demand, particularly in renewable energy, digital agriculture, and smart infrastructure systems. These sectors require higher levels of technical and digital competencies, thereby increasing the importance of continuous skill upgrading and lifelong learning mechanisms. The emergence of "Smart City" and "Smart Village" concepts reflects a broader shift toward knowledge-based regional development, where innovation, data-driven decision-making, and technological diffusion play a central role.

Despite these advances, the existing literature reveals a notable gap. Most studies focus either on the social dimensions of reintegration or on macro-level reconstruction policies, with limited attention to the integrated analysis of labor market dynamics, institutional capacity, and sectoral transformation. There is a lack of context-specific research examining how structural barriers, skill mismatches, and policy interventions interact within a unified economic framework in post-conflict regions.

This article seeks to address this gap by providing a comprehensive analysis of labor market reintegration in the liberated territories of Azerbaijan, focusing on the interplay between human capital transformation, demand-side dynamics, and institutional mechanisms. By situating the analysis within both theoretical and empirical frameworks, the study contributes to a more nuanced understanding of how post-conflict regions can transition from reconstruction-driven growth to a sustainable and productivity-oriented development model.

3. STRUCTURAL TRANSFORMATION OF THE REGIONAL LABOR MARKET IN THE POST-CONFLICT PERIOD

3.1. Demographic Profiles of Returnees and the Re-orientation of Human Capital

Historically, the Karabakh and East Zangezur regions occupied a fundamental position within Azerbaijan's agro-industrial complex, specializing in intensive agriculture, viticulture, animal husbandry and associated light processing industries. Under the Soviet planned economy, these territories were deeply integrated into a system of production cooperation and centralized resource allocation, where the division of labor was predominantly anchored in collective farming and state-led industrial enterprises. The conflict in the early 1990s and the subsequent mass displacement of the population effectively dismantled this regional economic fabric, severing production chains and geographically fragmenting the indigenous human capital. This rupture entailed not only the loss of physical capital but also the erosion of institutional memory and the functional mechanisms of the local labor market (Kərimov, 2025).

Over the ensuing three decades, the internally displaced population largely assimilated into the urban economies of Baku and other major cities, gravitating toward the service sector and informal employment. This process of urban adaptation catalyzed a structural transformation of human capital, leading to the gradual atrophy of original agrarian competencies and regional specializations. Post-2020, the restoration of these territories and the implementation of the "Great Return" strategy have inaugurated a new historical phase: the objective transcends mere physical resettlement to encompass the institutional and structural reintegration of these regions into the national economic system (Decree No. 3587 of the President of the Republic of

Azerbaijan "I State Program on the Great Return to the territories liberated from occupation of the Republic of Azerbaijan", 2022). The historical trajectory of labor resources and their transformative stages now serve as the primary analytical baseline for assessing the supply side of the labor market in the post-conflict era.

Prolonged displacement has exerted a direct influence on the structural and qualitative parameters of labor resources. According to human capital theory, skills and knowledge constitute investment-grade assets that undergo amortization when underutilized or decoupled from a compatible economic environment. A significant portion of the displaced population operated for decades outside their original vocational domains, often confined to low-productivity and informal employment. This phenomenon exacerbated qualification mismatches and diminished the functional value of human capital, leading to a decline in its market valuation (Awu, Darius, & Chimele, 2025).

In economic literature, the concept of "occupational scarring5" encapsulates the persistent negative impact of long-term unemployment or forced career shifts on future labor market performance. Within the context of displacement, these "scars" are both psychological and professional. The psychological component manifests as diminished risk appetite and weakened entrepreneurial initiative, while the professional component relates to the failure to update skills in alignment with the evolving technological conjuncture (Suphaphiphat & Shi, 2022). Reprioritization of labor resources becomes imperative, necessitating the transformation of existing skill sets to meet the requirements of the new regional economic model.

The demographic composition of the returning population is the principal factor determining the quantitative and qualitative characteristics of regional labor supply. The relative youth of the age structure provides a foundation for high labor activity and long-term productivity growth; however, this potential can only be realized if supported by commensurate levels of qualification and skill capital. Given that the younger generation's educational levels were shaped in urban settings with a predilection for the service sector, a skill inequality emerges upon their return to agro-industrial regions.

The labor behaviors of a young generation characterized by urbanized experience do not fully align with the physical and technical competencies demanded by agriculture and primary processing. This structural mismatch may destabilize the internal labor market balance, leading to inefficiencies in workforce allocation. Gender balance remains a critical determinant; the labor force participation rate of women dictates the socio-economic resilience of the region and defines the inclusivity of the endogenous development6 model. Without adequate institutional and social support mechanisms for female employment, the realized volume of labor supply will inevitably lag behind its statistical potential (Girdziute, et al., 2022).

The long-term development of post-conflict regions is inextricably linked to the re-orientation of human capital. The "Green Economy" and "Digital Agriculture" strategies envisioned for Karabakh and East Zangezur require a technologically intensive, knowledge-based approach that diverges from traditional agrarian models (Amanova, 2025). This necessitates not merely the restoration of existing skills but their radical reconfiguration.

[5] The long-term negative labor market outcomes (such as lower wages or higher unemployment risk) resulting from a period of forced displacement or unemployment.

[6] A development model that relies on the internal resources, skills and innovative capacity of a specific region rather than solely on external aid.

Lifelong learning mechanisms enhance the dynamic adaptability of labor resources and mitigate human capital amortization. A targeted, sector-specific design of vocational training programs ensures the optimal allocation of resources from the standpoint of economic efficiency. Synchronizing these training initiatives with regional priorities will catalyze labor productivity and accelerate structural transformation. The re-orientation of human capital must be evaluated not merely as social policy, but as an integral component of investment strategy.

The reprioritization of labor resources encompasses the enhancement of digital literacy, adaptation to agrotechnological innovations and readiness for green technology integration. Such an approach bolsters the endogenous development model and strengthens the sustainable integration of the region into the national economic framework.

The phenomenon of return migration from Baku and other urban centers can be analyzed through two economic lenses: as brain gain (the reversal of brain drain) or as mere demographic displacement. If returnees successfully transpose the managerial, service-oriented and digital competencies acquired in urban environments to the region, a genuine brain gain effect may materialize. However, should these skills fail to align with the regional economic structure, the return will result only in a quantitative increase in labor supply. While labor mobility enhances adaptability to shifting economic conjunctures and encourages efficient resource allocation, it is insufficient for sustainable reintegration on its own. The qualitative transformation of human capital and its alignment with regional priorities remain the decisive factors.

3.2. Transitioning from Infrastructure-Led Growth to Sustainable Sectoral Employment

The reconstruction of the Karabakh and East Zangezur economic regions represents one of the most capital-intensive post-conflict recovery initiatives in contemporary economic history. From a demand-side perspective, the initial phase of reintegration has been defined by massive state-led investments in physical infrastructure, including transportation networks, energy grids and "smart" urban settlements. While this infrastructure-led growth model is indispensable for establishing the foundational conditions for resettlement, its primary contribution to the labor market remains inherently transitory. The critical challenge for the Azerbaijani economy lies in managing the transition from the temporary labor demand generated by the construction surge to a sustainable, diversified and private-sector-driven employment framework.

Currently, labor demand in the liberated territories is overwhelmingly dominated by the construction, civil engineering and demining sectors. This phase creates a temporary employment surge driven primarily by public procurement. In macroeconomic terms, these state-led expenditures act as an exogenous shock to regional demand, stimulating local activity through the investment multiplier7 (Blanchard & Leigh, 2013).

However, historical precedents in post-conflict zones (such as the Balkans or Southeast Asia) suggest that economies often face a reconstruction bubble8. This phenomenon occurs when the labor demand for low-to-medium skilled manual labor peaks during the infrastructure phase and then sharply collapses once primary projects reach completion. To prevent this, the Azerbaijani government must synchronize the conclusion of major infrastructure projects with

[7] An economic mechanism where an initial increment in public or private spending leads to a proportionally larger increase in the overall regional income through successive rounds of spending.

[8] A transitory economic phenomenon where post-conflict labor demand and growth rates are artificially inflated by short-term, state-led infrastructure spending, risking a sharp contraction once primary physical restoration projects reach completion.

the operationalization of industrial and service sectors. Without this synchronization, the regional labor market could face significant frictional unemployment as workers displaced from construction sites struggle to find roles in more permanent, technology-intensive sectors. To circumvent a “boom-and-bust” cycle, the state’s role must evolve from being the primary employer via procurement to becoming a facilitator of market-led demand. This necessitates the strategic utilization of special economic zones and industrial clusters, such as the Aghdam Industrial Park and the Araz Valley Economic Zone[9]. These zones are designed to generate permanent labor demand by lowering entry barriers for firms through fiscal holidays, customs exemptions and integrated utility infrastructure.

This strategic intervention fosters a “crowding-in” effect[10], ensuring that public expenditures catalyze private sector participation rather than displacing it. In this context, demand is expected to shift toward the manufacturing of construction materials, the light industry and agro-processing. The localization of production not only reduces logistics costs but also ensures that the labor demand becomes an endogenous feature of the regional economy, rather than a byproduct of state budget cycles.

The demand side of the labor market is increasingly being shaped by the “Green Energy Zone” and “Digital Agriculture” concepts. Unlike traditional industrialization, the green economy is characterized by high capital intensity and a demand for specialized technical competencies. This shifts the regional labor demand curve toward high-quality human capital, requiring a profound synergy between industrial policy and vocational education standards.

The development of solar and wind energy potential in Kalbajar and Lachin creates a specific demand for renewable energy engineers and technicians. The “Smart Village” framework (exemplified by Aghali) redefines agrarian labor demand. The demand is no longer for traditional subsistence labor but for agrotechnologists, data analysts and supply chain specialists capable of operating IoT-based irrigation[11] and monitoring systems. The integration of these territories into national and global value chains depends on the ability of local enterprises to meet stringent export standards, which consequently fosters a demand for expertise in quality control, logistics and international trade regulations.

The sustainability of labor demand ultimately hinges on the risk-return calculus of private investors. Post-conflict regions often carry a significant risk premium[12] due to residual security concerns and initial market thinness[13]. To stimulate demand, the Azerbaijani government has introduced comprehensive institutional incentives, including ten-year fiscal exemptions, social insurance subsidies for regional employers and preferential loan schemes.

From the perspective of institutional economics, these incentives serve to “internalize the positive externalities” of regional development. By lowering the marginal cost of labor for

[9] A specialized industrial cluster established by presidential decree in 2021, strategically located in the Jabrayil district to leverage the logistics potential of the Zangezur corridor and serve as a regional hub for processing, logistics and technical services.

[10] A phenomenon where increased government spending or institutional incentives encourage and stimulate additional private sector investment rather than displacing it.

[11] An advanced precision agriculture framework that utilizes interconnected sensors and real-time data analytics to automate water delivery, optimizing resource efficiency and increasing crop yields through climate-responsive technology.

[12] The additional return or economic incentive required by investors to compensate for the perceived uncertainty and higher risks associated with operating in a post-conflict environment.

[13] A condition in a developing or post-conflict economy characterized by a low volume of transactions and a limited number of buyers and sellers, which results in high price volatility and reduced liquidity for labor and capital.

firms, the state encourages businesses to enter the market during its most uncertain phase. However, for this demand to remain sustainable in the long term, it must eventually transition from being subsidy-dependent to being productivity-driven. Regional competitiveness must be built on comparative advantages, ensuring that the labor demand remains robust even after the phase-out of initial fiscal incentives.

4. INSTITUTIONAL FRAMEWORKS AND STRATEGIC INCENTIVES FOR SUSTAINABLE ECONOMIC REINTEGRATION

4.1. Strengthening Labor Market Absorptive Capacity through Structural Alignment

In the post-conflict phase, the economic reintegration of the liberated territories is not limited solely to the restoration of physical infrastructure or sectoral investments. The fundamental issue is the labor market's capacity to integrate the newly returning population effectively. In this context, the concept of "labor market absorptive capacity" is not measured solely by the number of available vacancies; it is also determined by the alignment between the economic structure, institutional mechanisms and information flows (Cattani, Savoia, & Orlandi, 2024). The separate analysis of the supply and demand sides in previous sections indicates that the primary challenge for sustainable employment is the functional integration of these two dimensions. This integration can be secured through structural alignment.

Viewed through the lens of institutional economics, the labor market's absorptive capacity refers to the market's ability to accept, allocate and direct the new workforce toward productive activities. This involves more than just vacancy availability. It is linked to the reliability of contractual relations, the protection of property rights, the level of trust among market participants and the minimization of transaction costs.

Formal and informal institutions guide economic behavior and determine the efficiency of resource allocation. If the enforcement mechanisms for contracts in the labor market are weak, if uncertainty in labor relations is high, or if the share of the shadow economy has increased, the absorptive potential diminishes. In such cases, even the existence of jobs does not generate full employment because market subjects tend to be risk-averse.

Macroeconomic stability is also a prerequisite for absorptive capacity. Low and predictable inflation, fiscal discipline and currency stability stabilize investor decisions and ensure the continuity of labor demand. Otherwise, exogenous shocks create fluctuations in the labor market, leading to the postponement of long-term employment decisions (Blanchard, Dell'Ariccia, & Mauro, 2010).

Furthermore, the flexibility of the regional economic structure plays a vital role. If an economy depends on only one or two sectors, it cannot absorb the entire returning population. A diversified structure expands absorption opportunities by forming jobs suitable for various skill levels. Thus, the labor market's absorptive potential is shaped by the interaction of institutional quality, macroeconomic stability and sectoral balance. Structural alignment acts as the primary mechanism ensuring the coordination of these elements.

One of the primary problems in the liberated territories is qualification mismatch. A portion of the returning population has worked in service and informal sectors within urban environments for a long time, whereas the current economic structure of the region is oriented more toward agro-industry, logistics and energy sectors. This disparity creates a structural mismatch in the labor market, causing unemployment rates to remain artificially high.

Qualification mismatch manifests in two forms: horizontal and vertical. Horizontal mismatch occurs when an individual's field of specialization does not coincide with the fields demanded by the labor market. Vertical mismatch happens when the level of education and skills is either lower or higher than the requirements of available jobs. In both cases, an inefficient allocation of resources occurs and labor productivity declines (Verhaest & Omey, 2006).

To address this problem, reskilling and upskilling strategies are economically justified tools. Reskilling involves the complete re-formation of existing skills for an entirely new sector, while upskilling involves the deepening and refinement of current competencies. These processes can be evaluated as an investment in human capital.

According to economic models, when the internal rate of return for training programs is positive in the long term, it leads to a reduction in structural unemployment14. Although short-term costs are high, these investments are compensated in the medium and long term through increased labor productivity and the expansion of the tax base. The effectiveness of structural alignment depends on the coordination of training programs with the needs of the real sector. If educational modules are designed outside of market demand, a new mismatch arises. Therefore, sectoral analysis and labor market forecasting are essential components of this process.

Information inequality in the labor market is one of the main factors reducing employment efficiency. Employers lack complete information regarding the skills of potential employees, while job seekers face insufficient information about available vacancies and wage conditions. This situation leads to an increase in frictional unemployment15.

Asymmetric information raises transaction costs and delays the conclusion of labor contracts. Digitalized vacancy databases and integrated data platforms can mitigate this problem. If regional employment systems provide real-time information on vacancies, required skills and wage intervals, the alignment process accelerates.

Additionally, skill certification mechanisms serve as a signaling function for employers. Standardized assessment systems reduce uncertainty regarding worker quality and increase the probability of concluding labor contracts. This enhances market transparency and strengthens structural alignment.

The integration of digital skills formed in urban environments into the region's agro-industrial sector occurs through the mechanism of knowledge transfer. The knowledge spillover effect ensures the diffusion of new technologies and management practices into the local economic system. A young and technologically literate workforce drives innovations such as digital monitoring in agricultural production, logistics optimization and the implementation of e-commerce platforms. This process increases internal innovation potential in accordance with the endogenous development model. That is, economic growth stems from internal knowledge and technology diffusion rather than external capital.

[14] A form of involuntary unemployment caused by a fundamental mismatch between the skills that workers in the economy can offer and the skills demanded of workers by employers.

[15] The temporary unemployment that occurs when workers are in the process of moving from one job to another or are searching for jobs that match their specific skill sets.

Knowledge transfer leads to productivity growth and an increase in value-added. If this process is supported by through innovation clusters and technology parks, a sustainable employment structure will be formed in the region. Strengthening the labor market's absorptive capacity requires the coordination of structural alignment, information transparency and knowledge transfer mechanisms. The synchronous operation of these elements facilitates the formation of a sustainable and productive employment model by reducing the institutional gaps between the supply and demand sides.

4.2. Synergetic Effects of Public Employment Policies and "Smart" Regional Development

In the liberated territories, the state's employment policy acts not merely as a tool for social intervention, but as an economic mechanism that accelerates structural transformation. The primary objective of these policies, beyond ensuring the integration of the returning population into the labor market, is to foster a sustainable and highly productive economic model in the region. While the previous section analyzed institutional and structural barriers, this section focuses on how these barriers are overcome through specific fiscal and structural tools. The efficacy of state intervention should be measured not only by short-term employment growth but also by long-term productivity and competitiveness indicators.

The ten-year tax exemptions, subsidies for social insurance contributions and utility concessions applied to the liberated territories are essential elements of a classic fiscal incentive package. These tools directly reduce the marginal costs of enterprises and influence investment decisions.

In the microeconomic model of the labor market, the labor demand curve reflects the decisions of firms based on marginal productivity and wage levels. Subsidizing social insurance contributions reduces actual labor costs, creating a stimulus for firms to hire more employees. Expressed graphically, the labor demand curve shifts to the right. That is, more workers are hired at the same wage level (Cunha, Giorgi, & Jayachandran, 2019).

Tax exemptions function through a similar mechanism. Reducing corporate income tax increases the internal rate of return on investment, stimulating capital inflows into the region. This has an indirect effect on increasing labor demand. Through the fiscal multiplier effect16, initial state incentives create broader economic activity. If the multiplier coefficient is greater than one, each unit of state fiscal stimulus generates a larger increase in total output.

Utility concessions enhance attractiveness, particularly for energy-intensive and processing-oriented sectors, by reducing operating costs. This improves investment attractiveness and positively influences the formation of sectoral balance. However, the effectiveness of fiscal incentives depends on their duration and targeted nature. If incentives are broad but non-selective, the budgetary burden increases, potentially leading to inefficient resource allocation. Therefore, aligning incentives with specific sectoral priorities is crucial.

The "Smart Village" and "Smart City" concepts entail not only the construction of digital infrastructure but also the cluster-based organization of human capital. This model possesses the potential to trigger a technological leap in the economy.

[16] An economic concept where an increase in government spending leads to a proportionately larger increase in national income and economic activity.

The concept of a "human capital cluster" refers to the interaction of highly skilled labor, innovation centers and technology enterprises within a specific geographic area (Otsuka & Sonobe, 2018). In such clusters, the diffusion of knowledge and innovation17 occurs more rapidly due to the intensive flow of information among firms.

The smart village model encourages the application of digital technologies in agriculture sensor-based irrigation, drone monitoring and data analytics. This accelerates the transition from traditional agrarian employment to high-tech employment. As a result, labor market productivity increases and wage levels rise. The primary advantage of this model is its ability to bridge the structural gap between the agricultural sector and the digital economy. If agriculture is managed through technology-based systems, it no longer acts as a low-productivity sector but as an innovation-oriented field of activity. From the perspective of technological profitability, while smart infrastructure investments require high capital expenditure at the initial stage, they reduce operating costs and increase productivity in the long term, thereby strengthening the region's competitive advantage.

Active Labor Market Policies18 play a critical role in the region's structural transformation. Through self-employment programs, vocational training courses and specific quotas, the state accelerates the adjustment process in the labor market.

The effectiveness of these programs depends on their synchronicity with the needs of the real sector. If vocational training programs do not align with the skills demanded by the market, a "policy mismatch" risk arises. In such instances, state resources are utilized inefficiently and sustainable growth in employment indicators is not achieved.

Evaluation mechanisms play a decisive role here. Performance-based monitoring and outcome indicators allow for the measurement of program impact. If self-employment programs generate only short-term income but lack strong market integration, their long-term efficacy remains low. Aligning Active Labor Market Policies tools with regional priorities and sectoral forecasts reduces the risk of policy mismatch. In this case, state intervention complements market mechanisms without replacing them.

Forming the region as a "Net Zero" emission zone opens new opportunities for the creation of green jobs19. The transition toward a low-carbon economy generates demand not only for traditional technical positions but also for emerging specialties in renewable energy, energy efficiency, and environmental monitoring. These roles encompass a wide spectrum of skill requirements, ranging from engineers and technicians in solar, wind, and biomass energy systems to specialists in smart grid management and environmental compliance.

According to endogenous growth theory, investment in technology and human capital is the internal source of economic growth. The development of the green sector serves not only ecological goals but also stimulates innovation and knowledge-based growth. Green jobs create high added value and enhance the region's long-term competitiveness. If specialization in this field is achieved, the region can attain a comparative advantage.

[17] The process by which new technologies, practices, or ideas spread through an economic system or cluster.

[18] Government programs designed to help the unemployed find work through training, job search assistance and subsidized employment.

[19] Positions in sectors that contribute to preserving or restoring environmental quality, such as renewable energy, green construction and sustainable agriculture.

Consequently, the efficacy of state employment policy depends on the coordination of fiscal incentives, the smart regional development model and active labor market programs. The synergy of these mechanisms possesses the potential to form not only short-term employment growth but also a sustainable and high-tech economic structure.

CONCLUSİON

This research has systematically analyzed the formation of the labor market in the liberated territories of Azerbaijan within the context of macroeconomic reintegration. The analysis demonstrates that the economic recovery of the region transcends the mere reconstruction of physical infrastructure; the fundamental challenge lies in ensuring structural alignment between labor supply and labor demand. The transformation of human capital during the prolonged period of displacement, the acquisition of urban-centric skills and the emergence of new sectoral priorities have made an initial structural mismatch in the labor market inevitable. That the long-term competitive advantage of the liberated territories can only be secured through the alignment of human capital with sectoral priorities, the diversification of investment flows and the strengthening of institutional coordination. Economic growth will remain dependent on temporary fiscal stimuli, failing to establish a sustainable development trajectory.

That while the infrastructure-oriented growth model is necessary during the transition phase, it is insufficient for long-term employment. The multiplier effect of construction-based growth is limited and stagnates at a "transitory expansion" stage unless supported by sectoral broadening. Therefore, the creation of permanent jobs in manufacturing, logistics, tourism, processing industries and high-tech agricultural sectors must be a strategic priority.

Institutional absorptive capacity has a direct impact on economic growth. Without transparency in contractual relations, efficient information flow and the coordination of active labor market policies, the integration of supply and demand sides remains weak. Structural alignment mechanisms, such as reskilling, upskilling and information platforms are essential prerequisites for realizing the economy's productivity potential.

"Smart" and "Green" development models enhance the quality of the labor market. The Smart Village and Smart City concepts represent the formation of human capital clusters rather than just technological infrastructure. Green energy and digital agriculture sectors create high-value-added and technologically profitable jobs. This model strengthens the endogenous growth trajectory, establishing the region's long-term competitive advantage.

Sustainable labor market development in the liberated territories requires a coordinated policy framework that simultaneously aligns human capital formation, investment strategy, digital infrastructure, and sectoral priorities. Education and reskilling policies must be tailored to regional economic needs through the establishment of vocational centers focused on logistics, green energy, agrotechnology, and digital management, with modular training programs developed in partnership with employers to reduce structural mismatch. Investment policy should prioritize labor-intensive yet productive sectors, expanding logistics centers, agroparks, and processing industries through Public-Private Partnerships and targeted fiscal incentives that stimulate long-term capital formation and enhance the fiscal multiplier. Strengthening digitalization and institutional coordination through a unified regional employment ecosystem

and integrated “Smart” platforms for vacancies, skill profiles, and training opportunities will reduce information asymmetry, improve labor matching, and support data-driven monitoring.
The sustainable development of the labor market in the liberated territories requires strategic coordination, institutional adaptation and technological modernization. When synchronicity is ensured between human capital, investment flows and state policy, the macroeconomic reintegration of the region will transcend the recovery phase and transform into a new model of economic development.

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TEMPORAL INEFFICIENCIES IN RISK RECOGNITION: A CAUSAL ANALYSIS OF RISK PERCEPTION LAG IN GLOBAL BANKING SYSTEMS

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ABSTRACT

This paper develops a theoretical and empirical framework to measure Risk Perception Lag (RPL), the temporal distance between the objective realization of an economic shock and its subsequent incorporation into internal bank risk measurement and provisioning systems. Utilizing a comprehensive global panel of 320 commercial banks from 2011 to 2024, the author decomposes RPL into three structural dimensions: informational frictions, model inertia, and institutional delay. Methodologically, the study employs a two-step System GMM estimator to address the dynamic persistence and endogeneity inherent in risk recognition, alongside a Difference-in-Differences (DiD) design centered on the mandatory adoption of IFRS 9 and CECL. The results indicate that while the transition to forward-looking accounting has reduced average lag, structural inefficiencies, particularly rigid model recalibration cycles and governance complexity, continue to drive significant temporal gaps. Furthermore, the author finds evidence of an asymmetric "stigma effect" and forbearance incentives: banks are quick to recognize severe credit deteriorations to signal "kitchen-sinking" but delay the recognition of marginal deteriorations to prevent capital depletion. These findings provide critical insights for macroprudential surveillance, the calibration of countercyclical capital buffers, and the ongoing refinement of Basel IV and IFRS 9 frameworks.

Keywords: risk perception lag, System GMM, IFRS 9, loan loss provisions, bank governance, procyclicality, forbearance.
JEL Classifications: G21, G28, G32, M41, C23.

1. INTRODUCTION

The resilience of the global financial system is contingent not only on the magnitude of regulatory capital but also on the temporal efficiency with which institutions recognize emerging risks. Historically, banking research has focused predominantly on the precision of risk models and the volume of loan loss provisions (LLP). Yet, the 2008 global financial crisis and subsequent localized banking stresses revealed that the timing of risk recognition is often as critical as the accuracy of the final estimate (Hull, 2018; Bhattacharya et al., 2024). This paper formalizes the concept of Risk Perception Lag (RPL), representing the delay between the realization of an exogenous economic shock and its formal inclusion in a bank's internal reporting, provisioning, and capital planning systems.

The motivation for this study stems from the fundamental shift from the incurred loss" model of IAS 39 to the "expected credit loss" (ECL) frameworks under IFRS 9 and US GAAP CECL (IFRS Foundation, 2014; Basel Committee, 2019). While these reforms were explicitly intended to solve the "too little, too late" problem of risk recognition (Ryan, 2011; Beatty and Liao, 2014), recent empirical evidence suggests that implementation is far from frictionless (Behn and Couaillier, 2023). Heterogeneity in data pipelines, internal rating-based (IRB) model architecture, and corporate governance routines implies that banks face varied speeds in risk transmission, allowing discretionary delays to persist under the guise of model complexity (Huizinga and Laeven, 2012).

This paper argues that delayed risk recognition is not merely a technical artifact but an endogenous choice driven by capital constraints, governance friction, and managerial incentives to engage in supervisory forbearance or "zombie lending" (Caballero, 2008; Acharya et al., 2019). When banks delay the recognition of non-performing loans (NPLs), they artificially inflate their equity capital, staving off regulatory intervention but simultaneously freezing credit allocation to productive sectors (Diamond and Rajan, 2011).

This study contributes to the literature in three distinct ways. First, the author mathematically formalizes RPL, decomposing it into informational friction, model inertia, and institutional delay. Second, a robust causal identification strategy is introduced using a dynamic twostep System GMM estimator (Arellano and Bond, 1991; Blundell and Bond, 1998) to isolate structural delays from contemporaneous measurement error. Third, a Difference-in-Differences (DiD) is applied setting to test the exogenous shock of IFRS 9 implementation on RPL using a carefully trimmed dataset of 320 global banks spanning 2011-2024.

2. COMPREHENSIVE LITERATURE REVIEW

2.1. Accounting Regimes and Provisioning Discretion

The foundational literature on banking risk heavily scrutinizes the role of accounting regimes in shaping managerial behavior. Beatty and Liao (Beatty and Liao, 2014) and Bushman and Williams (Bushman and Williams, 2012) establish that managers utilize loan loss provisions not only to reflect credit risk but to manage earnings and regulatory capital. Under the incurred loss model, provisions were backward-looking, exacerbating procyclicality (Gaston and Song, 2014). The introduction of IFRS 9 and CECL was designed to front-load provisions (Abad and Suarez, 2017). However, Guenther et al. [2021] and Behn and Couaillier (2023) show that ECL models rely heavily on macroeconomic forecasts, injecting a new vector of subjectivity. If banks possess the discretion to select optimistic macroeconomic scenarios, the ”too little, too late” problem morphs into a “model inertia” problem.

2.2. Bank Governance, Information Processing, and Delay

Institutional design dictates how efficiently information flows from loan officers to the board of directors. Jiang et al. (2019) demonstrate that hierarchical complexity within banks slows down information processing, particularly for soft information. Furthermore, Laeven and Levine (2009) and Berger et al. (2016) highlight that bank governance – specifically the risk appetite of the board—significantly dictates the timeliness of loss recognition. Banks with weaker governance or entrenchment issues tend to exhibit higher opacity and longer delays in downgrading borrower credit ratings (Flannery, 2013; Naburgi, 2025).

2.3. Procyclicality, Forbearance, and Real Economic Effects

Delayed risk perception has real macroeconomic consequences. When banks fail to recognize losses promptly, they are incentivized to roll over bad debt – “zombie lending” – to avoid depleting capital (Caballero, 2008; Acharya, 2019). Diamond and Rajan (2011) argue that the fear of fire sales causes banks to hold onto illiquid, impaired assets longer than optimal. This regulatory forbearance (Gaston and Song, 2014; Becker and Ivashina, 2024) traps capital in unproductive sectors. Moreover, banks dynamically adjust their risk standards based on competition and the macroeconomic cycle (Ruckes, 2004; Begenau, 2018), meaning RPL is likely countercyclical: lengthening during the onset of a crisis as banks delay bad news, and shortening during recoveries.

3. THEORETICAL FRAMEWORK AND HYPOTHESES

3.1. Mathematical Formalization of RPL

Let $t_{shock\,it}$ be the exact moment an exogenous risk event occurs (e.g., a borrower defaults or an industry-wide macroeconomic shock hits). Let $t_{response\,it}$ be the moment the bank officially adjusts its capital provisions. RPL for bank i at time t is:

$$RPL_{it} = t_{response\,it} - t_{shock\,it} \qquad (1)$$

The author models the bank’s decision to recognize risk as a dynamic optimization problem. The bank aims to maximize the expected utility of its reported capital C_τ at recognition time τ, subject to a regulatory and market penalty for delayed recognition $\Phi(\tau - t_{shock})$.

$$\max_{\tau \geq t_{shock}} E\,[U\,(C_\tau)] - \Phi\,(\tau - t_{shock}) - \Omega\,(IF, MI, ID) \qquad (2)$$

Here, Ω represents the structural friction costs comprising:

1. **Informational Friction (IF):** Cost of verifying soft information (Stiglitz and Weiss, 1981).
2. **Model Inertia (MI):** The cost of out-of-cycle IRB recalibration.
3. **Institutional Delay (ID):** Governance bottlenecks requiring board approval for massive LLP shifts.

3.2. Hypotheses Development

Based on the theoretical friction parameters, the author formalizes the following hypotheses:

- **H1 (Informational Distance):** Banks with higher monitoring costs and greater geographic dispersion of asset portfolios exhibit a significantly larger RPL due to elevated IF.
- **H2 (Model Rigidity):** Banks utilizing through-the-cycle (TTC) rating models rather than point-in-time (PIT) models exhibit higher model inertia (MI), thereby increasing RPL.
- **H3 (Governance Efficiency):** An increased proportion of board members with dedicated risk management expertise reduces institutional delay (ID), accelerating risk recognition.
- **H4 (Capital Constraint / Forbearance):** Weakly capitalized banks exhibit an extended RPL during macroeconomic shocks, delaying recognition to prevent breaches of Basel minimum capital requirements (Gropp, 2014; Thakor, 2014).
- **H5 (IFRS 9 Shock):** The transition to IFRS 9 ECL models significantly reduced average RPL, but generated an asymmetric "stigma effect" where positive rating migrations are recognized much slower than negative ones.

4. DATA AND METHODOLOGICAL RIGOR

4.1. Sample Selection and Trimming

The dataset consists of an unbalanced panel of 320 commercial banks from 20 OECD countries over the period 2011–2024. Data is extracted from Orbis Bank Focus, matched with market data from Bloomberg and macroeconomic data from the World Bank.

Due Diligence Criteria: To ensure the validity of dynamic panel estimators, banks with fewer than four consecutive years of observations (Roodman, 2009) are excluded. To mitigate the effect of extreme outliers caused by mergers and acquisitions, all continuous bank-level variables are winsorized at the 1st and 99th percentiles.

Table 1.

Descriptive Statistics of Key Variables

Variable	Obs	Mean	Std. Dev.	P25	Median	P75
RPL (Days)	3,840	142.5	45.3	110.0	138.5	165.0
IF Cost (OpEx/Loans %)	3,840	2.45	0.88	1.80	2.30	2.95
MI Freq (Recalibrations/Yr)	3,840	1.75	0.95	1.00	2.00	4.00
Gov Exp (% Risk Experts)	3,840	18.5	8.2	12.0	18.0	25.0
ETA (Equity/Assets %)	3,840	8.55	2.15	7.10	8.40	9.80
NPL Ratio (%)	3,840	3.12	2.45	1.50	2.60	4.10
Size (Ln Total Assets)	3,840	16.5	1.8	15.2	16.4	17.8

4.2. Econometric Identification: System GMM

Bank governance, model calibration, and risk perception are highly endogenous; unobserved managerial quality simultaneously affects profitability and RPL. Furthermore, RPL exhibits path dependence (a bank that is slow to update this quarter is likely to be slow next quarter).

Therefore, static OLS or Fixed Effects models will yield biased, inconsistent estimates (Nickell bias).

The author employs the two-step System GMM estimator proposed by Blundell and Bond [12]. The specification is:

RPLit = αRPLit−1 + β1IFit + β2MIit + β3IDit + β4Shockt + γ′Xit + ηi + δt + ϵit (3)

where ηi captures unobserved time-invariant bank heterogeneity and δt controls for global macroeconomic shocks. Internal variables (IF, MI, ID, ETA) are treated as endogenous and instrumented with their own lagged levels in the differenced equation, and lagged differences in the level's equation (Roodman, 2009).

4.3. Difference-in-Differences (DiD) Specification

To isolate the regulatory shock (H5), the author leverages the staggered global rollout of ECL models (IFRS 9 in 2018 for Europe; CECL in 2020 for the US).

RPLit = θ0+θ1(Treati×Postt)+θ2(Treati×Postt×LowCapi)+γ′Xit+ηi+δt+ϵit (4)

Treat equals 1 for banks adopting IFRS 9 in 2018. LowCap is a dummy for banks in the bottom quartile of capitalization, testing the forbearance hypothesis.

5. EMPIRICAL RESULTS AND DISCUSSION

5.1. Baseline GMM Results: The Anatomy of Delay

Table 2 presents the core System GMM estimations. The coefficient on the lagged dependent variable (RPLt−1) is robustly positive (∼ 0.58), confirming severe persistence in risk reporting delays.

Table 2.

System GMM Regression Results: Determinants of RPL

Dependent: RPL_{it}	(1) Baseline	(2) Gov & Model			(3) Capital	(4) Full Model
		0.598***	0.602***	0.585***		
		(0.042)	(0.048)	(0.051)		
		–	–	0.132**		
				(0.058)		
		-2.10***	–	-1.95***		
		(0.55)		(0.62)		
		-0.455**	–	-0.442**		
MI Freq		(0.172)		(0.168)		
Gov Exp			(0.85)	(0.91)		
		1.20*	1.05	1.12*		
ETA (Capital)	–	(0.61)	(0.65)	(0.60)	- 3.12***	-2.85***
AR(1) p-value	0.012	0.014			0.011	0.015
AR(2) p-value	0.245	0.312			0.285	0.355
Hansen J p-value	0.412	0.485			0.455	0.512
Observations	3,840	3,840			3,840	3,840
Instruments	24	28			26	34

Notes: *Standard errors in parentheses. ***, **, and * denote significance at 1%, 5%, and 10% levels. AR(2) confirms no second-order serial correlation. Hansen J confirms instrument validity (avoiding instrument proliferation, keeping instruments ¡ groups).*

Supporting H1 and H2, high information friction (IF _Cost) increases the lag, while frequent model recalibration (MI _Freq) sharply decreases it. A 1 standard deviation increase in recalibration frequency reduces RPL by approximately 2 days. Supporting H3, risk expertise on the board accelerates recognition significantly. Crucially, supporting H4, higher capitalization (ETA) reduces RPL; conversely, weakly capitalized banks delay recognition by nearly 3 additional days per unit drop in capital, strongly validating the "forbearance" and capital preservation theories established by Diamond and Rajan (2011) and Kagerer et al. (2025).

5.2. IFRS 9 Exogenous Shock and Forbearance Incentives

Table 3 evaluates the DiD specification surrounding IFRS 9.

Table 3.

Difference-in-Differences: IFRS 9 Adoption and Strategic Delay

Outcome: RPL_{it}	Coefficient	Std. Error	*t*-stat
Treat×Post (Base IFRS 9 effect)	-14.45***	4.12	-3.50
Treat×Post×WeakGov	8.32*	4.45	1.87
Treat×Post×LowCap	11.15***	3.80	2.93
Bank Fixed Effects	Yes		
Time Fixed Effects	Yes		
Adj. R-squared	0.45		

Note. *IFRS 9 reduced average lag by 14.45 days. However, this efficiency gain is almost entirely offset (by +11.15 days) in banks with low capital buffers, indicating that ECL frameworks do not eliminate strategic managerial delay when survival is at stake.*

The baseline adoption of IFRS 9 successfully reduced RPL by roughly two weeks (14.45 days), corroborating the intended forward-looking nature of the regulation (Abad and Suarez, 2017). However, the triple interaction term (*Treat* × *Post* × *LowCap*) is highly significant and positive (11.15). This implies that vulnerable banks utilize the subjective macroeconomic forecasting inherent in IFRS 9 to "hide" behind optimistic scenarios, effectively neutralizing the regulatory intent and continuing to exhibit substantial risk perception lags.

6. ROBUSTNESS AND DIAGNOSTIC CHECKS

To ensure the credibility of the findings, several due diligence checks were conducted:

1. **Instrument Validity:** Following Roodman (2009), the author collapses the instrument matrix in the System GMM to prevent instrument proliferation, which can overfit endogenous variables and weaken the Hansen J-test. The instrument count remains strictly below the number of bank groups (N = 320).
2. **Parallel Trends Assumption:** For the DiD analysis, a pre-trend analysis was conducted by interacting the Treat dummy with time indicators for t − 3, t − 2, and t − 1. None of

the pre-treatment coefficients were statistically significant, confirming that treated and control banks were on parallel RPL trajectories prior to IFRS 9.

3. **Too-Big-To-Fail (G-SIB) Placebo:** The author interacted the main variables with a Global Systemically Important Bank (G-SIB) dummy. Interestingly, G-SIBs exhibit longer institutional delay (ID), suggesting that extreme hierarchical complexity in mega-banks offsets their superior IT and data infrastructures (Jiang, 2019).

7. CONCLUSION AND POLICY IMPLICATIONS

This paper introduces Risk Perception Lag as a vital empirical metric, arguing that in financial risk management, delayed truth is functionally equivalent to error. By rigorously mapping the structural transmission mechanisms of risk shocks into bank provisions, it is demonstrated that informational friction, rigid models, and complex governance inherently slow down risk recognition.

While forward-looking accounting standards like IFRS 9 have structurally reduced the average time-to-recognition, they have not eliminated the agency problems underlying banking. Specifically, the author finds robust causal evidence of capital forbearance: weakly capitalized banks exploit the subjective nature of ECL macroeconomic scenarios to delay the recognition of credit deterioration, engaging in stealth capital preservation.

For policymakers and supervisors, the implication is clear. Macroprudential stress tests and asset quality reviews (AQRs) must evaluate banks not just on the static level of their provisions, but on the dynamic velocity of their risk updating pipelines. Regulators should scrutinize out-of-cycle IRB recalibrations and board-level overrides, particularly during the onset of macroeconomic downturns, to prevent the crystallization of zombie lending.

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THE ROLE OF THE DATA PRODUCTS OF THE NATIONAL STATISTICAL OFFICES FOR DATA-DRIVEN POLICIES OF COUNTRIES (a case study from Iran)

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ABSTRACT

The data products of national statistical offices play crucial roles in developing data-driven policies for social and economic growth of countries. The data products such as the results of population census and economic statistics, provide policymakers with a clear picture of the existing conditions, a standard toolkit for measuring progress made towards accomplishing the national development plans, and a roadmap for future development plans. Considering the fact that data are produced at high volumes, varieties and velocities on different subjects, the national statistical offices must adapt themselves to keep up with the speed of data production, analyzing data in real-time, and disseminating high-quality data to the users. The Statistical Centre of Iran which has been approved as the provider of official statistics on the I.R. Iran provides its users and policy makers in Iran with data products such as results of population and housing census, agriculture census, the results of various surveys on industries, Iran statistical yearbook and main indicators of the economy of Iran. These data products are appropriate measurements of the progress made for promoting the quality of social and economic lives of Iranian citizens. In this paper, the characteristics of data products and data policy of the Statistical Centre of Iran are explained, and their roles are assessed based on their contribution to assessment and preparation of the data-driven development policies in Iran. The results of this paper show that the data products of the Statistical Centre of Iran which measure various economic and social activities conducted in Iran are true images of existing situation and can be used as a roadmap for future development plans and upcoming national reports on achieving sustainable development goals.

Key words: Data Product, Data Policy, National Statistical Offices

INTRODUCTION

The international recommendations on statistical activities and conducts encourage the national statistical offices of countries (NSO) to produce quality statistics by using concrete methodologies such as planning to use new data sources such as administrative and provide their various users with timely and quality statistics. It is recommended that all national entities should work closely with their NSOs when developing national indicators for assessing the quality of data and statistics in order to find out what data are available and which data can be collected in the future.

The NSOs are responsible to provide timely, accurate and quality data on different aspects of society and economy for their various users like authorities, researchers, businesspeople, and laypersons aimed at enabling them to make informed decisions. The NSOs also have the duty to ensure the users of the reliability and availability of quality statistics. The data products of the NSOs resulted from their activities are diverse such as survey data, census data, administrative data and dissemination products. It is obvious that these products pave the way for users to make decision based on the existing facts.

According to the United Nations Statistics Division, the NSOs exist to provide information to the general public, government, and the business communities in the economic, demographic, and environmental domains. The data products of NSOs can include census data, survey data, and administrative data. Census data provides a quantitative view on the economic, environmental and social conditions of the country. Survey data can be used to estimate population characteristics, such as employment, income, and education levels. The administrative data collected by government agencies, such as tax records, is used to produce official statistics. Moreover, the NSOs have been increasingly embracing non-survey data sources, such as satellite imagery and social media data, to supplement their traditional data collection methods[20]. These alternative data sources can provide timely and detailed information on various phenomena.

This paper is going to show the importance and role of the data products of the Statistical Centre of Iran (SCI), as the provider of official statistics on the I.R. Iran, in preparing the national data-driven policies of the Iranian government for social, economic and cultural development. For doing so, at the beginning of this paper, the works of various authors on the data products are explained. Then, the features of the data products of the SCI including data resulted from the population and housing census, the results of various surveys such as laboure force and consumer price index (CPI), Iran statistical yearbook and main indicators of the economy of Iran and also the data policy of the SCI are explained and their importance for development plans and programmes are illustrated in the following section. Then the development policies of Iran and their dependence on reliable and up to date data are presented. This paper concludes that reliable and quality data presented by the NSOs are prerequisites for development plans and assessment of their realization.

[20] https://hdsr.mitpress.mit.edu/pub/x0l4x099

1. LITERATURE REVIEW

Data products play an important role in the field of data science since they enable the organizations to effectively communicate insights and values of the organizations to stakeholders. Many scholars have studied the role and functions of data products.

DJ Patil (2012) defined data products as a product that facilitates an end goal through the use of data. O'Regan (2018) listed and grouped various types of data products as raw data, derived data, algorithms, decision support and automated decision-making.

The study by Pentland et al (2014) shows that data products can be categorized into three types: data-driven products, data-enriched products, and data-enabled products. Data-driven products use data as a primary source of value, while data-enriched products leverage data to enhance existing products or services. Data-enabled products use data to support the creation of new products or services.

Another study by Chen et al (2017) resulted that data products can lead to increased revenue and improved customer satisfaction. Manyika et al. (2017) conducted research on data literacy and highlighted the importance of data literacy in the development and deployment of successful data products.

In 2018, researchers from Singapore and Australia explored the concept of data products in the context of financial services. A study by Li et al (2018) proposed a framework for developing data products in the financial industry, highlighting the importance of data quality, analytics, and user engagement.

A study by Huang et al (2018) proposed a framework for developing data products, emphasizing the importance of data quality, visualization, and user engagement. Another study by Zhang et al. (2019) examined the role of data storytelling in data products, highlighting its impact on user understanding and decision-making.

Verhulst et al (2019) on their study on policy-data interaction found the challenges and opportunities of data-driven strategy development. The challenges include ethical and privacy concerns, while the opportunities include citizen-focused policy development and addressing public needs and preferences.

In 2019, researchers from Japan and South Korea examined the role of data products in enhancing customer experience in e-commerce. A study by Kim et al (2019) analyzed the impact of data products on customer loyalty and satisfaction in the e-commerce industry, suggesting that personalized data products can improve customer retention.

In 2020, the COVID-19 pandemic accelerated the development and deployment of data products, particularly in the healthcare sector. A study by Haghpanahi et al (2020) analyzed the use of data products in healthcare during the pandemic, highlighting their potential to improve patient outcomes and healthcare resource allocation.

In 2020, researchers from China and India investigated the applications of data products in healthcare and education. A study by Wang et al (2020) analyzed the use of data products in healthcare decision-making in China, highlighting their potential to improve patient outcomes and reduce healthcare costs.

Another study by Kumar et al (2020) examined the use of data products in education in India, suggesting that data-driven decision-making can improve student outcomes and educational effectiveness.

In 2021, researchers from Australia and New Zealand explored the challenges and limitations of data products. A study by Sivarajah et al (2021) examined the role of trust and perceived risk in data product adoption, highlighting the importance of building trust with users.
Akman et al (2021) conducted research on Turkey's open data policy and concluded that open accessible data in this country can be used to improve the public administration.
Lee et al (2021) analyzed the impact of data product complexity on user adoption and perceived value. They concluded that complex data products can be overwhelming for users.
In 2022, researchers from Taiwan and Hong Kong examined the applications of data products in sustainability and environmental management. A study by Lin et al (2022) analyzed the use of data products in sustainable supply chain management in Taiwan, highlighting their potential to improve environmental sustainability and social responsibility.
Another study by Wong et al (2022) examined the use of data products in environmental monitoring and management in Hong Kong. He suggested that data-driven decision-making can improve environmental protection and conservation.
More recent research has focused on the challenges and limitations of data products. A study by Wang et al (2022) examined the role of data product transparency in building trust with users, suggesting that transparent data products can improve user trust and loyalty.
Askarov et al (2022) in their study on significance of data-sharing policy used a Quasi-experimental difference analysis on economics journal and found that mandating data-sharing policies reduced publication bias.
Wang et al (2022) studied the relation between the data distortion and monetary policy in China's economy. Their research concluded that data manipulation and providing incorrect data in the China's economy can lead to incorrect monetary policy decisions and distorted macroeconomic outcomes.
Data policy refers to the rules and regularities of organizations for publishing and sharing their data assets. Data policies outline how companies and the NSOs collect data, what data can be collected, how data should be stored safe and for how long, and how the data is to be processed. The NSOs are in charge of providing correct, quality and comprehensive statistics in a timely manner for the policy makers in order to provide them with the needed materials for deciding on development policies aimed at promoting the quality of peoples' lives. Every organization which considers its data as a valuable asset is assumed to have developed a data policy which determines a roadmap to handle its data issues such as data definition, data access and authorization, data classification, data documentation, data security and data destruction.
Every NSO follows a data policy upon which the statistics resulted from various nationwide surveys such as population censuses are published for the users. Policies determined based on reliable and timely data pave the way for sustainable development which contributes to promotion of people's lives. Policy making would be fruitless if the provided data do not meet the prerequisites.
The data policy of the SCI is to diversify its data resources and use the modern technologies and methodologies in order to improve its data quality. For doing so, the SCI has established a work group including experts from different thematic offices on the data mining techniques and Big Data in the year 2015 based on the international recommendations. By considering the use of Big Data for production of official statistics, The SCI started to use this kind of data

directly for production of official statistics or indirectly for verification (macro edit), completion, matching, … At this time, the SCI is doing some activities based on Big Data such as a) Using of the open data on housing transactions for production of comparable statistics on price of housing and its transaction, b) Using of web scraping for production of statistics comparable with price indices statistics and c) Using of Instagram data for calculation of employment rate in the virtual business and macro edit of Labour Force Survey for calculation of unemployment rate. The cited statistics have not been published as official statistics and the SCI attempts to produce official statistics in these areas by changing its organizational structure based on the UN Handbook of Statistical Organization and becoming a process-based organization.

2. DEVELOPMENT PLANS IN IRAN

Iran has conducted ten development plans since the year 1963 with focus on socio-economic promotions. These development plans have played a significant role in shaping Iran's economic development and have contributed to the country's growth and progress over the years. The name, the characteristics and the main goals of these development plans are as follows:

The First National Development Plan was implemented between 1963 and 1968. Its primary objective was to facilitate industrialisation and infrastructure development in Iran. The plan's key projects included the construction of steel mills, cement factories, and hydroelectric power plants, which were designed to accelerate economic growth, boost industrial production, and enhance the living standards of the Iranian people.

The Second Development Plan (1968-1973) placed a greater emphasis on economic diversification and regional development. The primary objectives of this plan were to reduce the country's reliance on oil exports, to promote agricultural growth, and to develop regional industries. To achieve these goals, several significant projects were initiated, including the establishment of petrochemical complexes, the expansion of road networks, and the development of agricultural sectors.

The Third Development Plan, which focused on the development of heavy industry and economic growth, was conducted from 1973 to 1978. The plan was designed to achieve a number of objectives, including self-sufficiency in heavy industries, an increase in oil production, and an improvement in living standards. To this end, the authorities initiated a number of projects, including the construction of aluminium smelters, the expansion of steel production, and the development of nuclear energy.

The Fourth Development Plan, which was conducted from 1979 to 1984, had three main objectives: firstly, to revive the economy following the Iranian Revolution; secondly, to promote Islamic values; and thirdly, to reduce dependence on oil exports. The Fourth Development Plan was focused on economic reconstruction and the Islamicisation of the economy. In pursuit of these objectives, initiatives such as the nationalisation of industries, the establishment of an Islamic banking system, and the development of small-scale industries were implemented.

Following the conclusion of the war with Iraq, the initial five-year economic development plan was devised with a scheduled implementation period from 1989 to 1994. The overarching objective of this development plan was to facilitate the reconstruction and economic growth of Iran. In accordance with the primary objectives of reviving the economy following the Iran-

Iraq War, enhancing economic growth and improving living standards, a series of initiatives were implemented to reconstruct war-damaged infrastructure, expand oil and gas production, and develop transportation networks.

The Second Five-Year Economic Development Plan (1995-2000) was primarily focused on privatisation and economic liberalisation of Iran. The principal objectives of this plan were to enhance private sector involvement, encourage foreign investment, and enhance economic efficiency. In order to achieve these objectives, a number of national projects were initiated, including privatisation of state-owned enterprises, liberalisation of trade policies and the development of free trade zones.

The Third Five-Year Economic Development Plan (2000-2005) identified the issues of poverty reduction and human development in Iran. The key projects, such as the development of rural areas, the expansion of education and healthcare services, and the promotion of small-scale industries, were implemented with the objective of reducing poverty and unemployment, improving social welfare, and promoting human development.

The Fourth Five-Year Economic Development Plan (2005-2010) placed a strong emphasis on economic growth and the development of a knowledge-based economy. In order to achieve rapid economic growth, promote innovation and technology, and develop knowledge-based industries, the government implemented a series of key projects, including the development of information technology, the expansion of higher education, and the promotion of entrepreneurship.

The Fifth Five-Year Economic Development Plan (2010-2015) placed a strong emphasis on economic resilience and resistance economy. In order to achieve its stated objectives, namely enhancing economic resilience, reducing reliance on oil exports and fostering domestic production, the government initiated a series of development projects in strategic industries, expanded the use of renewable energy sources and promoted domestic tourism.

The Sixth Five-Year Economic Development Plan (2016-2021) placed a strong emphasis on economic growth, stability, and prosperity. The overarching objectives of this plan were to achieve sustainable economic growth, enhance economic stability, and foster prosperity. In order to achieve these objectives, a number of key projects were initiated, including the development of oil and gas industries, the expansion of transportation networks, and the promotion of foreign investment.

The most recent development plan in Iran is the Seventh Five-Year Economic Development Plan (2021-2026). This plan is focused on economic growth, innovation, and entrepreneurship. In order to achieve its overarching objectives, which include rapid economic growth, the promotion of innovation and entrepreneurship, and an improvement in the living standards of the population, the government has identified three key projects: the development of knowledge-based industries, the expansion of the digital economy, and the promotion of start-ups and small and medium-sized enterprises (SMEs).

3. THE KEY DATA PRODUCTS NEEDED FOR NATIONAL DEVELOPMENT PLANS

A review of the development plans carried out in Iran shows that these plans aimed at promoting the social and economic lives of people and improve the quality of their lives. It is crystal and clear that policy-makers needed timely and quality data in order to design, conduct, and assess their developed policies and plans. For assessing the macroeconomic and Fiscal aspects of the plans it is needed to have data on gross domestic product (GDP) and its components, gross national income (GNI), balance of payments data, and fiscal data such as government revenues, expenditures, and deficits. In order to assess the progress made for realizing the goals on poverty and social policy, the statistics on poverty rates and indicators, inequality measures, and data on access to social services like healthcare, education, and social protection come to the fore. For measuring the progress made for realizing goals on sectoral and industrial policies, the authorities should have data and statistics on production, employment, and trade data for key economic sectors, data on infrastructure, energy, and natural resource use. The data and statistics on trade and financial integration and external economic conditions and trends are needed to assess the progress made toward achieving the international economic relation of the country. National statistical systems play a crucial role in producing these essential data[21]. Adequate funding, capacity, and coordination are needed to strengthen national statistical systems and ensure data is used effectively in the policymaking process[22]. Based on the framework of the National Statistical Development Strategy (NSDS), more than 30 statistical surveys and data collection activities are carried out by the SCI for the purpose of production of statistics on different sectors of Iranian economy, industries, mining, agriculture, trade, services, energy, employment, housing and households. Furthermore, 105 statistical surveys have been conducted in order to collect the detailed information required for the input-output tables and ICT satellite accounts. Besides, for the purpose of decreasing the costs of surveys' implementation and accelerating the process of extraction of the survey results, paper questionnaires have been replaced with tablet in some of the SCI surveys. The Results of these surveys are available in the form of printed publications and also through the National Statistical Portal. Other Activities of the SCI include carrying out research projects in cooperation with the Statistical Research and Training Centre (SRTC), holding tens of national and international training workshops, preparation and compilation of several titles of classifications and statistical standards, and preparation of standard definitions and concepts in Persian for hundreds of statistical items. In this direction and based on the Paragraph A of the Article 54 of the Law on the Five-year National Social Economic and Cultural Development Plan, the SCI is the sole official authority eligible for preparation, announcement and dissemination of the official statistics in the country in order to integrate, organize and remove the parallel activities in the national statistical system of Iran. In this line, the SCI continuously follows the process of organizing the administrative organizations' registers and establishing and updating the National Statistical Information Database, as well as databases on time series, censuses, national accounts, etc. Promotion of statistical literacy throughout the society especially among the four groups of policy makers, users, respondents and producers of statistics, is one of the major goals of the SCI for which it is various programs in the form of National Statistical Development Strategy and the plans aimed at promotion of statistical literacy.

[21] https://www.econstor.eu/bitstream/10419/142039/1/cbn-jas_v1-i1-pp099-106.pdf

[22] https://www.oecd-ilibrary.org/sites/dcr-2017-6-en/index.html?itemId=%2Fcontent%2Fcomponent%2Fdcr-2017-6 en

The SCI uses the international recommended classification for conducting its surveys and census. These classifications are ISIC Rev.4[23], CPC Ver 2.1[24], ISCO 2008[25], COFOG[26], COICOP[27], COPNI[28], COPP[29], ICHA 2000[30], ICATUS 2016[31], ICLC[32], ISCED[33], SICTA[34], ICF 2001[35], CEPA 2000[36], M9 and M74.
Some of the most important statistical surveys of the SCI which are conducted in the form of census, sampling and register based surveys in various time intervals such as annual, biannual, quarterly and monthly basis as well as ad-hoc surveys, are National Population and Housing Census, National Census of Agricultural, Social and Economic Censuses of Nomadic Tribes.
Other statistical surveys including surveys on industrial establishments with 10 and more workers, operating mines, modern chicken farms (broiler, layer and pullet, breeder and hatcheries), livestock, horticultures, national tourists, research and development activities, trade establishments, labour force, time use, income and expenditure of urban and rural households, price and house rent in Tehran city, price and house rent in urban areas, producer price (industry sector, residential buildings in Tehran city, wholesale services, retail services, and price index surveys).
The main data products of the SCI resulted from its activities cover widespread social and economic subjects. The census data are presented at detailed level. The results of various surveys such as industrial cattle farms, national vessels, Poultry Meat supplied by the National Poultry Slaughterhouses and time use survey are published online. The main economic indicators which are updated by the SCI are CPI, PPI, decile inflation rate, Average Price of Consumer Goods and Services for National Households (Urban Area), national import and export indices, Quantity Indices of the Manufacturing, mining and Agriculture, unemployment rate, economic participation rate, population growth rate, Gini coefficient, population of the country, and economic growth rate.
The SCI also collects and disseminate statistics on various sections such as labour force, household expenditure and income, tourism, national accounts, culture, population, climate, environment, energy, transport, trade, price index, education, and time use. The Iran Statistical Yearbook contains the latest statistical information available on economic, social, cultural and political areas of the country to meet the statistical data needs of the local decision makers, planners and researchers, as well as all other interested users. The Yearbook has been released regularly since the year 1345. The major sources of the Yearbook include: (a) the results of

[23] The International Standard Industrial Classification
[24] Central Product Classification
[25] The International Standard Classification of Occupations
[26] Classification Of the Functions of Government
[27] The Classification of Individual Consumption According to Purpose
[28] Classification Of the Purposes of Non-Profit Institutions
[29] Code Of Professional Practice
[30] The International Classification for Health Accounts
[31] International Classification of Activities for Time-Use Statistics
[32] International Consensus Classification
[33] International Standard Classification of Education
[34] The Standard International Classification of Tourism Activities
[35] International Classification of Functioning, Disability and Health
[36] The Classification of Environmental Protection Activities

censuses and sample surveys conducted by the SCI, (b) the results of surveys conducted by other government organizations, and (c) administrative registers.

4. DATA PRODUCTS OF SCI FOR DEVELOPMENT PLANS AND POLICIES

A short review of the development policies and the data products of the SCI shows that the economic development plans which are aimed at stimulating economic growth often require comprehensive economic statistics and demographic data series. The Public health policies use data on population health statistics. The educational policies can be shaped using census records and statistics on literacy rates and school enrollment. The urban planning needs data on population density, housing, and infrastructure. The climate and environmental policies utilize data on natural resources, pollution levels, and energy consumption. A comparison between these statistical needs for development plans and policies in Iran and the data products of the SCI indicates that the data products of the SCI can be considered as the starting point and baselines for designing and assessment of these plans and policies.

One of the data products of the SCI is the Labour Force Survey, the results of which are published on a quarterly and annual basis. The objective of this survey is to obtain data pertaining to the composition and the current condition of the labour force, as well as to identify any changes that may have occurred. The aforementioned aim is accomplished through estimation on labour force at different levels (seasonal, annual, provincial and national). The two notions of employment and unemployment are necessary to assess the existing status of national economies. In other words, increase in employment rate is considered as an indicator for realization of development plan. The unemployment rate serves as an indicator for the appraisal of national economic conditions.

The compilation of statistics on minerals production represents the fundamental basis for a valuable supply chain that serves a variety of economic sectors, most notably the manufacturing and housing industries. Mines play a significant role in the creation of sustainable employment opportunities and the generation of value-added outputs within the economic landscape. The direct and indirect export of mineral products and industries constitute a significant proportion of the national economy. The availability of accurate and timely statistics on mining activities is essential for the optimal utilisation of the country's diverse and abundant mineral resources. An annual survey of operating mines in the country is conducted for the purpose of producing statistics and information regarding the functions of operating mines in the country, the calculation of its share in the national GDP, the production and value of mineral products, the amount and value of direct exports of mineral products, value added, the composition of the workforce, the extraction of minerals, the value of investments, and other related issues.

The SCI administers the survey on public parking as one of the surveys on transportation establishments in order to obtain the data necessary for the calculation of the transportation sector of the national and regional accounts. Furthermore, the SCI conducts surveys on travel institutes and companies, public weighbridges, the Survey on National Vessels, and cargo institutes and companies. These surveys are conducted as part of the larger effort to obtain data for the transportation sector of the national and regional accounts.

The SCI conducts the time use survey in order to obtain information on what activities people do to spend their time. This survey provide statistics on the social and behavioral activities of the households.

The one of the important sub-divisions of agricultural sector is the activities related to crop's growing. These activities account for 50 percent of value added of this sector. The SCI has conducted the survey on crops growing activity aimed at collecting data to compile national accounts for the agriculture sector.

One of the censuses which the SCI carries out is the National Agriculture Census. This Census uses the IT devices (tablet) for gathering and registering the data on agricultural holdings. The results of this Census are valuable information on sub-systems of agriculture such as agricultural activities, horticulture, husbandry (light and heavy cattle), green house cultivation, planting, aquaculture (warm water fish and cold-water fish), apiculture.

The "Statistical Yearbook of Iran" is one the most important statistical publication of the SCI which reflects the statistics on different social and economic aspect of lives in Iran. The SCI also has established the National Statistical Information Database of Iran in 2002, accessible through the National Statistical Portal at www.amar.org.ir. This database is updated regularly and users have access to time series of statistics on different subjects such as employment, price index, and etc.

5. DATA POLICY AND STATISTICAL DISSEMINATION POLICY OF THE SCI

A further aspect of the SCI data policy is the information security policy. The SCI serves as the central entity within the Iranian statistical system, with the objective of coordinating the collection and dissemination of official statistics, and establishing a register-based statistical system that adheres to the fundamental principles of official statistics. The SCI provides users with up-to-date and reliable statistics, collected using appropriate and high-quality methodologies. These statistics are published at the earliest opportunity using comprehensive information dissemination methods and taking account of the confidentiality of statistics. In line with its obligation to provide services for users, the SCI is required to fully protect the results of censuses, surveys and administrative registers, which are considered to be one of the most valuable assets of the National Statistical System.

The organisational strategy and risk management framework of the SCI provides an appropriate context for the identification, monitoring, assessment and management of risks related to the data security of the SCI. This is achieved through the establishment and maintenance of an Information Security Management System (ISMS). This is achieved by taking into account the standards pertaining to the confidentiality, accuracy and accessibility of the information assets of the SCI.

The overarching objective of the SCI's information security policy is to guarantee the confidentiality, accuracy and integrity of statistical data. It is the responsibility of the SCI to safeguard the personal data of individuals (natural and legal persons) and their privacy in a manner that preserves the confidentiality of the statistical unit and restricts access to macro-level information to authorised personnel and institutions.

The Statistical Dissemination Policy of the SCI has been developed on the basis of seven principles namely as the guarantee of equal access to information, professional independence, transparency, confidentiality of statistical information, punctuality and timeliness, commitment to an information pricing policy, the adherence to the information system. These constituents on the SCI's statistical dissemination policy is the key path to public trust in the published official statistics in Iran.

6. CONCLUSION

The objective of this study was to ascertain the role and impact of data products from National Statistical Offices (NSOs) on the formulation of data-driven policies in countries. The data required for this research was the data products of the SCI, which serves as the as the provider of official statistics on the I.R. Iran. The SCI's primary activities include the promotion of statistical literacy and awareness, as well as the production of reliable, diverse, integrated, comprehensive, and comparable statistical data, ensuring quality and impartiality in this regard. These activities are realised through the various data products that this organisation makes available to the public and policy makers. This study examined the various data products of the SCI, which are the indicators of the different aspect of lives in Iran as well as the progress made toward achieving the development plans in Iran. Several data products of the SCI, including the results of multiple surveys on population, labour force, industrial sections, population census, agriculture census and Iran Statistical Yearbook, were assessed and their characteristics were explained. Furthermore, the development plans implemented in Iran were delineated, along with their ultimate objectives and pivotal projects designed to achieve those objectives. Ultimately, it was demonstrated that the data products of the SCI are capable of furnishing the requisite data for policymakers to assess the progress made and provide them with a roadmap for preparing future development plans.

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