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The economic implications of shadow AI in Georgia's public sector

Irakli Manvelidze*
Doctor of Public Administration, Professor
Shota Rustaveli State University of Batumi
6010, 35/32 Ninoshvili Str., Batumi, Georgia
https://orcid.org/0000-0001-6422-2049

Abstract. The purpose of this study was to systematically investigate the scale, drivers, and economic implications of Shadow AI in Georgia's public sector, and to propose evidence-informed policy interventions for enhancing AI readiness, workforce productivity, and fiscal risk mitigation. Although over 70% of public servants globally use AI tools, systematic empirical research on unauthorised "Shadow AI" in Georgia is lacking. To address this gap, a convergent mixed-methods design was employed, including a survey of 322 public servants, 15 semi-structured interviews, a three-round Delphi panel with 12 experts, a Ministry of Internal Affairs case study, and systematic document analysis. Quantitative survey data, qualitative interviews, and Delphi panel inputs were integrated to achieve methodological triangulation. Findings showed that 52.8% of public servants use AI tools (17.4% daily), while 42.9% engage in Shadow AI. Institutional readiness is limited: only 14.3% have a formal AI policy, 61.5% received no AI training, and 54% enter sensitive data into AI platforms. Thematic analysis identified five patterns: Silent Innovation, Double Standard, Training Desert, Data Fear, and Lack of Trust. Logistic regression shows that perceived productivity gains ($OR = 2.34$, $p < .01$) and absence of formal policy ($OR = 3.12$, $p < .001$) are significantly associated with Shadow AI adoption. These findings suggested coexisting productivity gains and unmitigated institutional risks, including inefficiencies from unmanaged AI use, uneven human capital development, and fiscal exposure from data breaches or algorithmic errors. The study suggested a contextual adaptation of the Unified Theory of Acceptance and Use of Technology (UTAUT), providing evidence that in transition economies perceived usefulness may outweigh absent facilitating conditions. For policymakers and public administrators, the research proposes four actionable interventions: mandatory AI literacy programs, a regulatory sandbox for controlled experimentation, AI Champions networks for peer support, and revised performance evaluation systems. These recommendations are designed to enhance economic efficiency, mitigate fiscal risks, and promote responsible governance in Georgia and comparable post-Soviet transition economies

Keywords: digital transformation; generative AI; institutional readiness; data privacy; UTAUT model; administrative efficiency; transition economies

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*Corresponding author (irakli.manvelidze@bsu.edu.ge)

Introduction

AI is increasingly transforming public sector operations worldwide, reshaping workforce productivity, administrative efficiency, and service delivery models. While global adoption of AI tools among public servants is accelerating, institutional readiness for their effective governance remains uneven, particularly in transition economies. This growing gap between individual-level adoption and organisational capacity raises important concerns regarding economic efficiency, fiscal risk, and administrative accountability.

Existing evidence suggests that AI use in the public sector is already widespread, with over 70% of public servants globally reporting engagement with AI tools in their daily work, according to Mission Square Research Institute (2025). However, institutional readiness remains limited, as many governments lack the capacity to effectively regulate and integrate these technologies (Barcelona Provincial Council, 2025). In Georgia, this challenge is particularly pronounced. Although AI diffusion has reached 18.2% of the workforce in 2025 (Microsoft, 2025), the country still ranks 87th in the Government AI Readiness Index (Oxford Insights, 2025), indicating a structural imbalance between technological adoption and institutional preparedness. This divergence may result in inefficiencies, uneven human capital development, and fiscal risks associated with unmanaged AI use. Institutional assessments confirm these limitations. IDFI (2021) indicated that formal AI governance frameworks in Georgia remain underdeveloped, with limited regulatory definitions and weak oversight mechanisms. Although Georgia has engaged with international governance initiatives, including the Council of Europe's AI Convention, implementation gaps remain significant (IDFI, 2024a).

At the workforce level, capacity constraints are also evident. A large proportion of public servants have not received formal AI-related training, and only a small share operates within institutions that have established AI governance policies, as was noted by E. Tskhvariashvili (2025). This increases the likelihood of informal or unregulated AI use in public administration. Importantly, discrepancies between official data and actual practice have been identified by national oversight institutions. The Public Defender of Georgia (2025) reported significant gaps between officially reported AI usage and actual practices within public institutions, suggesting that the true scale of AI adoption may be underestimated in formal statistics.

A growing concern in this context is the phenomenon of "Shadow AI", defined by R. Farrell (2025) as the unsanctioned or unregulated use of AI tools within organisational settings. While this phenomenon has been widely discussed in advanced economies, empirical evidence from transition contexts, such as Georgia, remains limited. Shadow AI presents a dual dynamic, simultaneously contributing to productivity gains while introducing risks related to data security, accountability, and decision transparency. The phenomenon of Shadow AI is not unique to Georgia but reflects a broader regional challenge. A large-scale study in Latvia (N = 1,557) revealed that more than half of public sector employees express limited trust in AI-generated information, with only seven participants out of 1,557 fully trusting AI. Furthermore, G. Lāma & A. Lastovska (2025) found that employees who received formal AI training rated their competence significantly higher than those without training. Given these challenges, there is a need to better understand how AI is adopted in Georgia's public sector, what competencies are required for its responsible use, and how institutions should adapt to emerging technological realities.

However, existing literature on Shadow AI presents two unresolved debates. First, while some studies such as J. Waters-Lynch *et al.* (2024) emphasise organisational control and formal governance as necessary responses, others, such as R. Farrell (2025), suggest that informal adoption may drive innovation that formal channels suppress. Second, evidence from advanced economies dominates the field, with limited attention to how weak institutional environments – characterised by absent policies, fragmented governance, and low AI literacy – shape Shadow AI dynamics. This study engages with both debates by examining a transition economy context where institutional constraints may paradoxically accelerate informal adoption while magnifying associated risks. The purpose of this study was to systematically investigate the scale, drivers, and economic implications of Shadow AI in Georgia's public sector, and to propose evidence-informed policy interventions for enhancing AI readiness, workforce productivity, and fiscal risk mitigation. Accordingly, this study addressed the following research questions: what is the scale of AI diffusion in Georgia's public sector, and how can Shadow AI be empirically conceptualised; what competencies are required for the effective and responsible use of AI among public servants; how do institutional factors influence patterns of AI adoption and governance in the public sector and what policy measures could enhance AI readiness and economic efficiency in Georgia's public administration.

Materials and Methods

This study adopted a convergent parallel mixed-methods design, following the methodological frameworks proposed by J.W. Creswell (2014) and A. Bryman (2016). Quantitative survey data, qualitative interview data, and Delphi panel inputs were integrated to achieve methodological triangulation across multiple sources of evidence. The research design was structured to address four interrelated research questions concerning the scale of AI diffusion, the prevalence of Shadow AI, workforce competencies, administrative adaptation, and policy instruments in Georgia's public sector.

A survey of 322 public servants was conducted between September and November 2025 using a stratified random sampling approach. The sampling frame encompassed all public institutions in Georgia, with an estimated total public sector workforce of approximately 32,000 employees.

Stratification was based on three dimensions: institution type (central government ministries, local government municipalities, and independent agencies), geographic location (Tbilisi metropolitan area, regional centres, and rural areas), and hierarchical level (senior management, middle management, and frontline staff). The sample composition was compared against available population parameters, showing reasonable alignment on institutional type but overrepresentation of Tbilisi-based respondents relative to regional distribution. Consequently, findings are best interpreted as indicative rather than statistically representative of the entire public sector workforce.

The survey instrument consisted of 25 items measured on five-point Likert scales (1 = strongly disagree to 5 = strongly agree), covering five domains: demographic characteristics; frequency and purposes of AI use; training experiences and needs; institutional readiness and policy environment; and Shadow AI behaviours alongside risk awareness. Pilot testing with 20 public servants yielded a Cronbach's alpha coefficient of $\alpha = 0.87$, indicating a high level of internal consistency across the instrument. Data were collected using Google Forms, achieving an overall response rate of 65.8% following three follow-up reminders. A brief non-response bias check compared early versus late respondents across key demographic variables (institution type, geographic location); no statistically significant differences were detected ($p > 0.10$ for all comparisons), suggesting that non-response does not substantially distort the findings. All surveys and parts of research, involving people, were conducted in accordance with ethical research principles, including voluntary participation, informed consent, confidentiality, and anonymity of respondents, in line with the principles of the Declaration of Helsinki (World Medical Association, 1964).

Statistical analysis was conducted using SPSS version 28. The analytical strategy included descriptive statistics, independent-samples t-tests, one-way analysis of variance (ANOVA), chi-square tests of independence, Pearson correlation analysis, and binary logistic regression, following established guidelines (Field, 2018). Table 1 presents the theoretical framework linking each research question to its corresponding conceptual foundation.

Table 1. Theoretical framework correspondence to research questions

Research Question	Theoretical Component
1. Scale of AI diffusion and Shadow AI	Shadow IT/AI (Waters-Lynch *et al*., 2024; Farrell, 2025)
2. New skills and competencies	TAM/UTAUT (Davis, 1989; Venkatesh *et al*., 2003; OECD, 2026)
3. Adaptation of administrative system	Diffusion of Innovations (Rogers, 2003); Digital Era Governance (Dunleavy *et al*., 2006)
4. Policy instruments for Georgia	Digital Era Governance + EU AI Act (IDFI, 2024a); Council of Europe Convention (IDFI, 2024b)

Note: the table presents the conceptual linkage between the study's research questions and the theoretical frameworks applied. Shadow AI is interpreted as an extension of Shadow IT literature; TAM/UTAUT explain technology adoption behaviour; Digital Era Governance and Diffusion of Innovations inform institutional adaptation; and policy instruments are derived from European regulatory frameworks and governance models
Source: compiled by author

Fifteen semi-structured interviews were conducted online via Zoom, each lasting between 45 and 90 minutes. Participants were selected through purposive sampling to ensure diversity of perspectives and included agency heads ($n = 3$), information technology managers ($n = 4$), human resource specialists ($n = 3$), and frontline AI users ($n = 5$). The interview protocol covered five thematic areas: current AI use practices and tools; perceived benefits and risks; training experiences and needs; perspectives on governance and policy requirements; and barriers to responsible AI use. Data saturation was systematically assessed and reached after the twelfth interview, with no substantially new themes emerging in the remaining three interviews. Transcripts were analysed using thematic analysis in accordance with V. Braun & V. Clarke's (2006) six-phase framework, resulting in the identification of five principal themes: Silent Innovation, Double Standard, Training Desert, Data Fear, and Lack of Trust.

A three-round Delphi panel involving 12 experts was conducted to validate empirical findings and to develop consensus-based policy recommendations. Experts were selected based on predefined inclusion criteria: a minimum of five years of professional experience in public administration ($n = 6$), academic expertise in AI ethics or digital governance ($n = 4$), or experience in public sector training and capacity development ($n = 2$). In the first round, participants were presented with preliminary findings and asked to evaluate their significance on a five-point scale. The second round provided anonymised feedback and invited participants to revise their assessments. The third round aimed to achieve consensus, which was defined a priori as at least 70% of experts assigning a rating of 4 or 5 on the five-point importance scale.

A case study of Georgia's Ministry of Internal Affairs examined an AI-based automated document processing system in operation since 2023. The analysis focused on compliance with relevant international frameworks, including the EU AI Act (IDFI, 2024a) and the Council of Europe Framework Convention on Artificial Intelligence (IDFI, 2024c). Key dimensions of assessment included: the presence of risk assessment procedures; transparency and disclosure mechanisms; audit trail requirements; and the existence of human oversight.

Systematic document analysis complemented the primary data collection. Sources included reports and policy documents from IDFI (2021), the Government of Georgia (2024), Microsoft (2025), Oxford Insights (2025), E. Tskhvariashvili (2025), the European Commission (2025), the Public Defender of Georgia (2025) and relevant institutional policies where available. The study received ethical approval from the Research Ethics Committee of Shota Rustaveli State University of Batumi. All participants provided informed consent and were assured of anonymity and confidentiality. Participation was voluntary, and respondents retained the right to withdraw at any stage without penalty.

Several limitations should be acknowledged when interpreting the findings. First, the sample (N = 322) represents approximately 1% of the total public sector workforce in Georgia, which limits the statistical generalisability of quantitative results. The findings are therefore best understood as indicative rather than definitively representative. Nevertheless, the stratified sampling design – based on institution type, geographic location, and hierarchical level – enhances representativeness within the constraints of a single-country study, and methodological triangulation strengthens the robustness of qualitative insights. Second, the cross-sectional design captures data at a single point in time; longitudinal research would be required to assess temporal dynamics in AI adoption and any causal relationships. Third, self-reported data may be subject to response bias, particularly in relation to unauthorised AI use, where underreporting is possible. Fourth, the size of the Delphi panel (n = 12), while consistent with established methodological practice, remains relatively limited, and the ROI estimates derived from it should be treated as expert-informed illustrations rather than precise economic forecasts.

Results and Discussion

The survey results indicate that 52.8% of Georgian public servants use AI tools, with ChatGPT, Microsoft Copilot, and Google Gemini identified as the most frequently used platforms. Among these users, 17.4% report daily use, 35.4% weekly use, and the remainder report monthly or occasional use. Document summarisation represents the most common application (78.2%), followed by email and report drafting (65.9%), data analysis (41.2%), and idea or budget generation (35.3%). These usage patterns are broadly consistent with international evidence reported by the Mission Square Research Institute (2025) and the Barcelona Provincial Council (2025). Table 2 summarises the principal indicators of AI use and associated risks.

Table 2. Main indicators of AI use and associated risks

Aspect	Data (%)	Theoretical interpretation	Main risk
Scale of AI use	52.8	TAM – perceived usefulness	-
Shadow AI	42.9	Shadow AI (Farrell, 2025)	Data leakage; reduced accountability
Daily AI use	17.4	UTAUT – performance expectancy	-
Document summarisation (users)	78.2	TAM – perceived ease of use	Hallucinations (67% do not verify outputs)
Email/report writing	65.9	UTAUT – social influence	Personal data exposure (54%)
Data analysis	41.2	Lack of facilitating conditions	Analytical inaccuracies (38% report low trust)
Idea/budget generation	35.3	Diffusion of innovations – early adopters	Informal use practices
Written AI policy	14.3	Absence of facilitating conditions	Governance gap
No AI training	61.5	OECD (2026) – skills barrier	Inconsistent and potentially unsafe use

Note: TAM = Technology Acceptance Model; Percentages are based on the survey sample (N = 322). Risk indicators reflect self-reported behaviours (e.g., lack of verification of AI outputs, input of personal data, and low trust in analytical accuracy) and are interpreted in relation to existing theoretical frameworks on technology adoption and governance. "Absence of facilitating conditions" refers to the lack of organisational support structures such as formal policies, training, and oversight mechanisms

Source: calculated by author based on survey data

The predominance of document summarisation and report drafting suggests that AI is primarily used for routine information-processing tasks that traditionally require substantial time investment. Interview data indicate that users may save approximately 2-3 hours per day through these applications. Economic productivity estimation: sensitivity and scenario analysis. Based on a conservative baseline estimate, in which 52.8% of public servants save an average of 1.5 hours per day, the aggregate productivity gain is estimated at approximately 25,000-30,000 labour hours per day across the public sector. Assuming an average public sector wage of approximately GEL 15 per hour (≈USD 5.50) (Geostat, 2025), this corresponds to an estimated daily productivity value of GEL 375,000-450,000 (≈USD 135,000-165,000), or approximately GEL 100-120 million annually (≈USD 36-44 million). To address the inherent uncertainty in these estimates, a scenario analysis was conducted using three variants (Table 3). The pessimistic scenario assumes that self-reported time savings are overestimated by 50% due to social desirability bias. The optimistic scenario assumes that underreporting of AI use (qualitative evidence suggested reluctance to disclose) means actual savings are 50% higher. The baseline scenario represents the direct calculation from survey data. Across all three scenarios, even the pessimistic estimate suggests substantial productivity gains (GEL 50-60 million annually), while the optimistic estimate reaches GEL 150-180 million. This range (GEL 50-180 million) should be understood as the plausible interval rather than a precise point estimate.

Table 3. Sensitivity analysis of estimated annual productivity gains

Scenario	Assumption (hours saved per user)	Annual productivity value (GEL million)
Pessimistic (lower bound)	0.75 (50% of baseline)	50-60
Baseline (central estimate)	1.5	100-120
Optimistic (upper bound)	2.25 (150% of baseline)	150-180

Source: author's calculations based on Table 2 indicators and Geostat (2025)

Uncertainty and methodological caveats. These estimates should be interpreted as illustrative and indicative, not as precise fiscal accounts, for five reasons. First, they rely on self-reported data, which may be subject to recall bias and social desirability bias (particularly for unauthorised AI use). Second, the assumption of GEL 15 per hour average wage is a simplification that does not account for variation across job grades, institution types, or geographic locations. Third, the estimate assumes that saved hours translate directly into productive work – an assumption that may not hold uniformly across all roles. Fourth, the cross-sectional design captures a single point in time; productivity effects may change as AI tools evolve. Fifth, because much of this activity occurs outside formal governance structures, these productivity gains are not systematically captured, measured, or reinvested at the institutional level.

This reliance on self-reported data reflects a deeper institutional reality documented by UNESCO (2026): Georgia remains at a foundational governance stage with no dedicated AI law, regulatory authority, or national strategy. UNESCO identifies a "dual bottleneck" – institutional constraints alongside technological gaps – which explains why objective, system-level data on AI-driven productivity do not yet exist. In the absence of centralised monitoring, self-reported data constitute the only feasible source. Triangulation with interviews and Delphi panel ($\alpha = 0.87$) partially mitigates subjectivity. Moreover, because much of this activity occurs outside formal governance structures, these productivity gains are not systematically captured, measured, or reinvested at the institutional level.

When asked specifically about using AI without formal authorisation or approval from information technology departments, 42.9% of respondents answered affirmatively. This figure aligns closely with findings reported by E. Tskhvariashvili (2025), providing cross-study validation. Qualitative evidence suggests that actual levels of unauthorised use may be higher, as several interview participants (P7, P11, P13) indicated reluctance to disclose such practices in formal survey settings. From a risk management perspective, this proportion corresponds to approximately 13,700 public servants operating outside formal governance frameworks.

Indicators of institutional readiness reveal substantial limitations. Only 14.3% of respondents reported the existence of a formal AI policy within their organisation, while 61.5% indicated that they had received no AI-related training. Additionally, 54% of respondents acknowledged entering personal or sensitive data (including citizen information and internal documents) into AI platforms without formal guidance or authorisation. These findings suggest the presence of a governance and training gap with potential economic implications. Each instance of personal data input into unregulated AI systems may represent a compliance risk under emerging regulatory frameworks. While enforcement mechanisms in Georgia are still evolving, alignment with European regulatory standards implies potential exposure to financial liabilities in the future. At the same time, the absence of structured training indicates that AI-related human capital is developing informally, without standardisation or quality assurance mechanisms.

A binary logistic regression analysis was conducted to examine factors associated with Shadow AI use (coded as 1 = yes, 0 = no). Independent variables included perceived productivity gain, AI training (binary), presence of a written policy (binary), and supervisor support. The results indicate that perceived productivity gain ($OR = 2.34$, 95% CI [1.58, 3.47], $p < .01$) and absence of a written policy ($OR = 3.12$, 95% CI [1.95, 4.99], $p < .001$) are significantly associated with Shadow AI adoption. In contrast, AI training ($OR = 0.89$, $p = .42$) and supervisor support ($OR = 1.12$, $p = .31$) were not statistically significant. The model as a whole was statistically significant ($\chi^2(4) = 38.47$, $p < .001$), with a Nagelkerke pseudo R^2 of 0.31 and an overall classification accuracy of 74.3%. These associations should be interpreted as correlational rather than causal, given the cross-sectional design.

Interpreting these regression findings, individual-level productivity incentives and the absence of formal institutional frameworks emerge as the primary factors associated with Shadow AI use. This pattern suggests a partial divergence from the Unified Theory of Acceptance and Use of Technology (UTAUT), which posits that facilitating conditions – such as organisational support, training, and infrastructure – directly influence technology adoption (Venkatesh *et al.*, 2003). While the absence of a formal AI policy is significantly associated with Shadow AI use ($OR = 3.12$), variables such as training and supervisor support were not statistically significant. This indicates that in contexts characterised by weak institutional frameworks, perceived usefulness – operationalised as productivity gains ($OR = 2.34$) – may play a dominant role in shaping user behaviour. Public servants appear to adopt AI tools primarily based on their perceived efficiency benefits, rather than organisational encouragement or formal support structures.

This finding suggests a contextual adaptation of UTAUT: in transition economy contexts, perceived usefulness may partially substitute for absent facilitating conditions. However, this substitution is not neutral in its effects. It introduces a divergence between individual-level incentives and organisational-level risk management. From an economic perspective, this dynamic can be interpreted through a principal-agent framework. Individual public servants (agents) maximise private benefits (time savings), while potential risks – such as data breaches or accountability failures – are externalised to the state (principal). This creates a form of negative externality, whereby privately rational behaviour may lead to suboptimal outcomes at the organisational or systemic level. Accordingly, technology acceptance models applied to public sector contexts may benefit from incorporating considerations of incentive alignment, institutional constraints, and risk externalities.

Turning to the qualitative evidence, thematic analysis of interview data identified five principal themes with distinct organisational and economic implications. The first theme, Silent Innovation, reflects the widespread informal use of AI tools without formal approval. Ten out of twelve AI-using interviewees reported engaging in such practices. One participant (P11) noted: "I use ChatGPT to summarise all my reports… it saves me two to three hours a day. I am hesitant to disclose this because there is no formal policy". This pattern suggests that productivity gains are realised at the individual level but are not systematically integrated into organisational processes.

The second theme, Double Standard, captures ambiguity in managerial responses to AI use. Leaders neither formally endorse nor explicitly prohibit AI adoption, resulting in unclear accountability structures. This dynamic may increase organisational exposure to risk while simultaneously allowing productivity gains to continue informally. The findings indicate a notable discrepancy between managerial support (22.4%) and actual AI use (42.9%), suggesting a gap between formal leadership positions and employee practices. From a governance perspective, such ambiguity may weaken accountability structures and limit the effectiveness of risk management processes. Standard frameworks, such as ISO 31000, emphasise the importance of explicit risk identification, assessment, and acceptance. In the absence of clear policy direction, risks may remain unarticulated and unmanaged. This situation may also generate agency costs, including reduced monitoring capacity, limited enforceability of standards, and potential misalignment between organisational objectives and individual behaviour. In economic terms, the decentralised capture of productivity benefits alongside the socialisation of risks resembles a common-pool resource problem, where incentives for individual optimisation may lead to collectively suboptimal outcomes.

The third theme, Training Desert, reflects the widespread absence of formal training opportunities. The majority of respondents rely on self-directed learning, which may lead to uneven skill development and inconsistent application of AI tools. The coexistence of high AI usage (52.8%) and limited training provision (61.5% without training) indicates that informal learning mechanisms are operating at scale. However, such learning processes are inherently uneven and may not align with best practices in data protection, ethical use, or output validation. For example, the finding that a substantial proportion of users do not systematically verify AI-generated outputs highlights potential risks associated with overreliance on automated systems. This is consistent with international evidence on AI hallucinations and user overconfidence (Hall, 2025). From a human capital perspective, this situation can be interpreted as a coordination problem in skills investment. While individuals invest time in acquiring AI-related competencies, the absence of institutional frameworks reduces the overall efficiency and reliability of this investment. Formal training programmes could enhance the social return on these skills by ensuring standardisation, risk awareness, and knowledge diffusion across the workforce. Moreover, the distributional dimension of this skills gap warrants attention, as qualitative evidence suggests that access to informal AI learning opportunities may vary across demographic and professional groups, potentially reinforcing existing inequalities.

The "Training Desert" phenomenon identified in Georgia is consistent with findings from Latvia, where a survey of 1,557 public servants demonstrated that AI training significantly increases self-assessed AI competence. Notably, more than half of Latvian respondents expressed limited trust in AI-generated information, with only 0.45% (seven participants) reporting complete trust in AI (Lāma & Lastovska, 2025). This corroborates current finding that the absence of structured training (61.5% of Georgian respondents) may directly contribute to both low competence and low trust, creating a barrier to responsible AI adoption.

The fourth theme, Data Fear, highlights awareness of data protection risks among users, which does not necessarily prevent AI use. Participants demonstrated partial understanding of risks but often prioritised efficiency under time constraints. The fifth theme, Lack of Trust, emerged primarily among non-users, who expressed concerns about the reliability and accuracy of AI outputs. This scepticism may limit broader adoption and reduce potential productivity gains.

These concerns are not unique to Georgia. As T. Cantens (2025) argued, the distrust in generative AI within public administrations stems from its limited explainability, which fundamentally restricts its appropriate use in the public sector. The risks surrounding confidentiality, the marking of AI outputs, and the potential for errors require both technical and cultural responses, pushing the boundaries of our instrumental conceptions of machines. Moreover, the transformative impact of GenAI on the intellectual production of the state raises fears of the replacement, or rather "enslavement", of civil servants to machines. T. Cantens (2025) therefore advocated for the development of critical thinking as a specific skill for civil servants who must learn to think with an eclectic machine.

While the potential benefits of generative AI in the public sector are widely recognised (Aryfiyanto & Alamsyah, 2024), the case study of the Ministry of Internal Affairs' automated document processing system indicates that the system operates without several key governance mechanisms, including formalised risk assessment procedures, transparency disclosures, audit trails, and clearly defined human oversight. Under the EU AI Act framework (IDFI, 2024a), such systems would likely be classified as high-risk and subject to specific regulatory requirements. The absence of these mechanisms may increase operational and compliance risks, although precise financial implications cannot be determined without further data.

A recent survey of 576 public managers across seven EU countries found that the unregulated or 'shadow' use of generative AI tools is widespread, particularly in contexts where formal governance mechanisms are still in their early stages (Tangi *et al.*, 2026). While earlier research has developed taxonomies to understand the phenomenon of Shadow IT (Kopper & Westner, 2016), shadow AI" acquires particular importance in the context of public administration, as it is associated not only with technological but also with institutional, ethical, and governance challenges (Silic & Back, 2014). M. Silic *et al.* (2025) noted that the "generative, opaque, and autonomous" nature of generative AI has turned Shadow AI into a "sociotechnical governance failure". The authors emphasise that AI tools such as ChatGPT and Microsoft Copilot are often used outside the boundaries of organisational IT control, creating a so-called "governance drift zone" – a situation where formal policies and regulations exist nominally but do not function effectively in practice.

The prevalence of Shadow AI, supported by both quantitative (42.9%) and qualitative evidence, suggests that it should be understood not as isolated individual behaviour but as a systemic organisational phenomenon. The identified themes – particularly Silent Innovation and Double Standard – indicate the emergence of an informal equilibrium in which AI use is tacitly tolerated but not formally regulated. This configuration may generate several economic implications. First, productivity gains remain decentralised and difficult to scale. While individual users report time savings, the absence of institutional coordination limits the ability to replicate and standardise successful use cases across agencies. Second, cumulative risk exposure may increase over time. The widespread input of potentially sensitive data into AI systems without formal safeguards introduces compliance and operational risks. While precise financial implications remain uncertain, alignment with international regulatory frameworks suggests the potential for future fiscal exposure. Third, informal learning pathways may lead to uneven human capital development. Fourth, the absence of institutional mechanisms for knowledge sharing may limit innovation spillovers.

The eight countries in Table 4 were selected to ensure representative geographic and institutional coverage of the post-Soviet space while maintaining comparability and avoiding excessive table size. Selection followed three principles. First, one country was chosen from each major post-Soviet subregion: the Baltics (Estonia), Eastern Europe (Ukraine, Moldova, Belarus – capturing variation in EU alignment), the South Caucasus (all three countries – Georgia, Azerbaijan, Armenia – included to enable intra-regional comparison), and Central Asia (Kazakhstan as the regional leader). Second, the selection spans the full range of AI readiness from Estonia (rank 21) to Belarus (rank 121), allowing systematic comparison of high, medium, and low performers. Third, the inclusion of EU candidate states (Ukraine, Moldova) alongside non-candidate states (Belarus, Azerbaijan) enables tentative observation of whether European institutional alignment is associated with higher AI governance capacity. All selected countries share a common Soviet administrative legacy but have diverged in their post-1991 governance reforms, digital transformation pathways, and international integration trajectories.

Table 4. Georgia in comparative perspective with post-Soviet states

Country	Subregion	Rank	Strategy	Capacity	Infrastructure	Governance	Public Sector Adoption
Estonia	Baltics	21	54.29	90.00	99.63	46.01	64.38
Ukraine	Eastern Europe (EU candidate)	41	52.40	83.00	80.24	40.34	58.21
Moldova	Eastern Europe (EU candidate)	71	61.50	56.67	82.33	22.40	61.06
Kazakhstan	Central Asia	58	53.88	64.63	73.59	39.85	37.38
Azerbaijan	South Caucasus	69	51.45	60.00	66.97	36.08	56.35
Georgia	South Caucasus	87	49.35	74.17	47.44	27.24	34.63
Armenia	South Caucasus	103	41.02	56.75	57.40	24.37	27.75
Belarus	Eastern Europe (non-EU)	121	12.00	43.38	24.03	24.62	36.88

Source: Oxford Insights (2025), Government AI Readiness Index (2025)

The data reveal several important patterns. Estonia (rank 21) leads the region across all pillars, particularly in Infrastructure (99.63) and Capacity (90.00), reflecting its long-standing digital governance investments. This aligns with the "AI Leap" initiative, which systematically builds AI competencies across the workforce. Ukraine (rank 41) demonstrates remarkable resilience, with high Infrastructure (80.24) and Public Sector Adoption (58.21) scores despite ongoing conflict. Ukraine's Diia.AI platform – the world's first national AI assistant for government services – validates this institutional capacity, processing over 200 public services with 70% of legal work handled by AI before human review (Sampson, 2025).

Moldova (rank 71) presents an interesting case. Despite a relatively low Governance score (22.40) – similar to Georgia's Governance (27.24) – Moldova achieves a much higher Public Sector Adoption score (61.06), second only to Estonia in this comparison. This pattern suggests that Moldova's ongoing EU accession process and its FAIMA AI Antenna initiative (providing access to EU supercomputing infrastructure) may be accelerating public sector AI adoption even in the absence of strong domestic governance frameworks. However, this interpretation remains tentative given the cross-sectional nature of the index data.

Kazakhstan (rank 58) and Azerbaijan (rank 69) show moderate performance, with Azerbaijan outperforming Georgia notably in Public Sector Adoption (56.35 vs 34.63). This suggests that despite similar regional constraints, Azerbaijan may have achieved greater diffusion of AI tools across its public workforce, though causal mechanisms cannot be established from these data. Georgia (rank 87) presents a distinctive profile. Its Infrastructure score (74.17) is relatively strong – second only to Estonia among the eight countries. However, Georgia's Strategy score (49.35) and Governance score (27.24) are among the lowest in the comparison group. More strikingly, Georgia's Public Sector Adoption score (34.63) is the lowest among all eight countries – even below Belarus (36.88) and Armenia (27.75, which is lower but Armenia ranks 103 overall). This pattern independently corroborates the central finding of current survey. The Oxford Insights data confirm that while Georgia has built reasonable digital infrastructure (74.17), it lacks the strategic frameworks (49.35) and governance mechanisms (27.24) to translate this infrastructure into actual public sector AI adoption (34.63). This aligns with the "dual bottleneck" identified in current qualitative analysis – the themes of Silent Innovation and Double Standard emerge from weak governance, not from technological gaps.

Belarus (rank 121) ranks lowest among the eight countries, with very low Strategy (12.00) and Infrastructure (24.03). However, its Public Sector Adoption score (36.88) slightly exceeds Georgia's (34.63), suggesting that even under autocratic governance and with minimal strategic frameworks, some degree of AI diffusion may occur – albeit likely in an unregulated "Shadow AI" pattern similar to Georgia. Armenia (rank 103) ranks second lowest overall but shows a more balanced profile, with Governance (24.37) and Public Sector Adoption (27.75) more closely aligned with its Strategy (41.02) than in Georgia's case. This suggests that Armenia's lower overall ranking reflects broader capacity constraints, whereas Georgia's underperformance is specifically concentrated in governance and adoption.

From a policy perspective, these findings suggest that Georgia's priority could be governance reform and strategic framework development, rather than additional infrastructure investment. Estonia's example demonstrates that high governance quality (46.01) – not just infrastructure – enables effective AI adoption. Conversely, Moldova's case suggests that EU integration and access to shared AI infrastructure may accelerate adoption even when domestic governance remains weak – a potential pathway for Georgia to consider. Evidence from the Public Defender of Georgia (2025) supports this interpretation, highlighting discrepancies between officially reported and actual AI use across public institutions. The finding that only a small number of agencies formally acknowledge AI usage, despite evidence of broader implementation, suggests the presence of institutional blind spots in governance and reporting mechanisms. From an economic perspective, this configuration reflects a dual dynamic: the coexistence of latent productivity gains and unmitigated institutional risk exposure.

The findings highlight three interrelated areas requiring policy attention. First, the development of AI-specific competencies is essential. Transitioning from general digital literacy to AI literacy – including skills such as prompt design, critical evaluation, and ethical awareness – may enhance both productivity and risk mitigation. Second, the establishment of formal governance frameworks is necessary to reduce uncertainty and manage risks. This includes the development of policies addressing data use, accountability, transparency, and oversight mechanisms. Third, leadership capacity could be strengthened to ensure that AI adoption is aligned with organisational objectives. This involves clarifying responsibilities, integrating AI into performance management systems, and fostering a culture of responsible innovation. Based on the empirical findings and validated through the Delphi panel process, four integrated policy recommendations are proposed. Each recommendation is grounded in an economic rationale linking the intervention to potential improvements in workforce productivity, human capital development, and fiscal risk mitigation (Table 5). These recommendations should be understood as evidence-informed possibilities rather than definitive policy prescriptions.

Table 5. Estimated potential economic impact of recommendations (expert-informed illustration)

Recommendation	Estimated cost	Estimated potential benefit	Illustrative horizon
Mandatory AI literacy	$50-100 per employee	~$500 per employee/year (based on Estonia)	6-12 months
Regulatory sandbox	$50,000-100,000	Risk reduction; potential productivity gains	12-18 months

Table 5, Continued

Recommendation	Estimated cost	Estimated potential benefit	Illustrative horizon
AI Champions network	$500-1,000 per Champion	Faster adoption; reduced errors	~6 months
Revised performance metrics	Minimal	Potential productivity improvement (20-30%)	3-6 months

Note: estimates are based on Delphi panel consensus (n = 12 experts) and economic productivity analysis. These figures are expert-informed illustrations rather than precise empirical forecasts. The ROI estimates should be interpreted as indicative ranges, not as guaranteed outcomes. Estonia's AI literacy investment figures are drawn from M. Voog (2025)
Source: compiled by author

Recommendation 1. Mandatory AI literacy for all public servants. Compulsory AI literacy training could be introduced for all public servants within a 12-month implementation horizon. The training curriculum could include foundational AI concepts, prompt engineering, critical evaluation of AI outputs, hallucination recognition, data ethics, bias detection, security protocols, and relevant legal frameworks, including the EU AI Act and the Council of Europe Convention. A structured training programme (estimated at 8-12 hours per employee) may contribute to reducing error rates associated with unverified AI outputs, improving data handling practices, and enhancing efficiency through more effective use of AI tools. Comparative evidence from Estonia suggests that an investment of approximately USD 50 per employee in training may be associated with productivity gains of around USD 500 per employee annually (Voog, 2025). However, these figures are context-specific and may not be directly transferable to the Georgian context.

Recommendation 2. Regulatory sandbox for controlled experimentation. A regulatory sandbox for AI experimentation could be established to provide a controlled and legally compliant environment for AI use within the public sector. The sandbox framework should clearly define categories of prohibited data and permitted data. With a current Shadow AI prevalence of 42.9%, the introduction of a sandbox mechanism may help formalise existing practices by offering a structured alternative to unauthorised use. International experience, such as the Delaware AI Sandbox initiative, suggests that sandbox approaches could reduce informal AI usage while preserving productivity benefits (State of Delaware News, 2025).

Recommendation 3. AI champions network for peer support. A cross-agency AI Champions network could be established to support the diffusion of AI capabilities and promote responsible use practices. Champions would receive advanced training beyond foundational literacy and act as internal facilitators. Each AI Champion (estimated ratio: one per 50-100 employees) would require approximately 40 hours of advanced training (costing approximately $500-1,000 per Champion), while providing ongoing support to a broader group of users at relatively low marginal cost.

Recommendation 4. Revised performance metrics. Existing performance evaluation systems could be updated to reflect the realities of AI-enabled work environments. Revised metrics might include indicators such as AI literacy certification, demonstrated critical evaluation of AI outputs, effective reallocation of time toward higher-value activities, and adherence to ethical and data protection standards. Aligning performance metrics with AI-enabled workflows may help mitigate unintended disincentives for adoption and encourage more efficient use of technology. While Georgia currently experiences a "Shadow AI" phenomenon characterised by unregulated individual adoption, neighbouring Ukraine has pioneered a different trajectory – the "agentic state". Ukraine's Diia.AI (n.d.), recognised as the world's first national AI assistant for government services, serves 23 million citizens and processes over 200 public services, with 70% of legal work within the Ministry of Digital Transformation handled by AI before human review (Sampson, 2025). This suggests that the evolution from unmanaged AI use to institutionalised AI integration is possible, but would require strategic investment in digital infrastructure and governance capacity – areas where Georgia's Government AI Readiness Index ranking of 87th indicates considerable room for improvement.

The study contributes to the literature in three main ways. Empirically, it provides one of the first systematic mixed-methods analyses of AI use and Shadow AI in Georgia's public sector. Theoretically, it suggests a contextual adaptation of the Unified Theory of Acceptance and Use of Technology (UTAUT) by providing evidence on how institutional readiness constraints shape technology adoption in transition economies. Practically, it offers evidence-informed policy recommendations aimed at strengthening AI governance, workforce capacity, and public sector efficiency.

Conclusions

This study provides the first systematic empirical evidence on the use of artificial intelligence and the prevalence of Shadow AI within a post-Soviet public sector. The findings reveal that a majority of Georgian public servants use AI tools, with approximately 40% engaging in unauthorised use. A substantial majority lack formal training, and written AI policies exist in only a small minority of organisations. Complementary evidence suggests that officially reported AI usage substantially understates actual practice, highlighting gaps in institutional visibility and governance.

Taken together, these results point to a structural imbalance between rapid technological adoption and comparatively limited institutional readiness. From an economic perspective, this imbalance may reduce the efficiency and sustainability of AI adoption in the public sector. The regression analysis identifies perceived productivity gain and absence of formal policy as factors significantly associated with Shadow AI use – both with odds ratios exceeding two – suggesting that individual efficiency incentives may outweigh institutional constraints in shaping behaviour. This finding suggests a contextual adaptation of the UTAUT framework, indicating that perceived usefulness may support technology adoption even when facilitating conditions are weak. However, given the cross-sectional design, these associations should not be interpreted as causal.

The absence of structured training may limit the long-term development of human capital and reduce the overall efficiency of AI utilisation. At the same time, informal and unregulated use practices may increase exposure to risks associated with data handling, accountability, and decision-making processes. While the magnitude of potential fiscal impacts remains uncertain, the findings indicate that unmanaged AI adoption may limit productivity gains while increasing operational and fiscal risks.

The findings provide new empirical grounding on Shadow AI in transition economies, extend UTAUT for contexts with limited institutional support, and offer actionable policy directions. Investing proactively in governance, skills, and organisational systems may boost productivity and reduce institutional vulnerabilities. Georgia's experience illustrates a broader dynamic relevant to many transition economies: rapid technological uptake can outpace institutional adaptation. Bridging this gap is essential for sustainable and effective public sector AI adoption.

Subsequent studies should prioritise four directions. First, longitudinal research is needed to track Shadow AI dynamics as institutional frameworks mature and to assess whether formal policies are associated with reduced unauthorised use over time. Second, comparative analyses across post-Soviet transition economies would help assess the generalisability of the proposed UTAUT adaptation. Third, quantitative risk assessment models should be developed to estimate potential fiscal exposure from data breaches, algorithmic errors, and non-compliance with emerging regulatory frameworks such as the EU AI Act. Fourth, experimental or quasi-experimental studies evaluating the effectiveness of specific interventions – including regulatory sandboxes, AI Champions networks, and mandatory literacy programs – would provide more definitive causal evidence to guide policy decisions. Future comparative research should examine the applicability of the proposed UTAUT adaptation in neighbouring transition economies, including Latvia.

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Conflict of Interest

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Економічний вплив «тіньового ШІ» на кадровий потенціал державного сектору Грузії

Іраклі Манвелідзе
Доктор публічного управління, професор
Державний університет імені Шота Руставелі в Батумі
6010, вул. Ніношвілі, 35/32, м. Батумі, Грузія
https://orcid.org/0000-0001-6422-2049

Анотація. Метою цього дослідження було проаналізувати економічний вплив штучного інтелекту (ШІ) на робочу силу державного сектору Грузії, зосереджуючись на прирості продуктивності, ризиках для зайнятості та інституційній адаптації. Хоча понад 70 % державних службовців у світі використовують інструменти ШІ, систематичні емпіричні дослідження несанкціонованого використання «тіньового ШІ» (Shadow AI) у Грузії відсутні. Для заповнення цієї прогалини застосовано конвергентний змішаний дизайн дослідження, який включає опитування 322 державних службовців, 15 напівструктурованих інтерв'ю, трьохраундову експертну панель Delphi (12 експертів), кейс-стаді Міністерства внутрішніх справ та систематичний аналіз документів. Кількісні дані опитування, якісні інтерв'ю та результати Delphi-панелі були інтегровані для забезпечення методологічної триангуляції. Результати показують, що 52,8 % державних службовців використовують інструменти ШІ (17,4 % – щоденно), тоді як 42,9 % залучені до практик Shadow AI. Рівень інституційної готовності є обмеженим: лише 14,3 % установ мають формальну політику щодо ШІ, 61,5 % не проходили жодного навчання з ШІ, а 54 % вводять конфіденційні дані в AI-платформи. Тематичний аналіз виявив п'ять ключових патернів: «мовчазні інновації», «подвійні стандарти», «навчальна пустеля», «страх даних» і «дефіцит довіри». Логістична регресія показує, що сприйняття підвищення продуктивності ($OR = 2.34$, $p < .01$) та відсутність формальної політики ($OR = 3.12$, $p < .001$) суттєво пов'язані з використанням Shadow AI. Отримані результати свідчать про одночасне існування зростання продуктивності та неврегульованих інституційних ризиків, включаючи неефективність через неконтрольоване використання ШІ, нерівномірний розвиток людського капіталу та фіскальні ризики, пов'язані з витоками даних або алгоритмічними помилками. Дослідження пропонує контекстуальну адаптацію Уніфікованої теорії прийняття і використання технологій (UTAUT), демонструючи, що в перехідних економіках сприйнята корисність може переважати відсутність сприятливих умов. Для політиків і публічних адміністраторів запропоновано чотири практичні інтервенції: обов'язкові програми з AI-грамотності, регуляторна «пісочниця» для контрольованого експериментування, мережі AI-чемпіонів для взаємної підтримки та перегляд систем оцінювання ефективності. Ці рекомендації спрямовані на підвищення економічної ефективності, зниження фіскальних ризиків та розвиток відповідального управління в Грузії та аналогічних пострадянських перехідних економіках

Ключові слова: цифрова трансформація; генеративний ШІ; інституційна готовність; конфіденційність даних; модель UTAUT; адміністративна ефективність; перехідні економіки