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Article

Beyond Adoption: A Composite AI Governance Maturity Index for Systemically Important Banks

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Abstract: The rapid uptake of artificial intelligence (AI) in credit scoring, investment decisions, and risk management has outpaced the ability of regulators and bank boards to validate it, a concern that is acute for systemically important banks (SIBs), where an inadequately governed model can transmit losses across the financial system. Existing diagnostic tools are either technology-focused AI maturity models or principle-based supervisory frameworks such as the NIST AI Risk Management Framework, ISO/IEC 42001, and the Basel Committee's D-SIB principles, none of which is designed to assess whether a specific SIB has the organisational capability to understand, control, and, if necessary, halt its own AI-driven credit and investment processes before they cause financial damage. This paper introduces the Composite AI Governance Maturity Index (CAGMI), built on eight weighted governance blocks, thirty-two threshold-scored indicators, and non-compensable "red-line" restrictions, and applies it as a documentary and illustrative exercise to Uzbekistan's seven SIBs, which held 62.4% of banking-sector assets and 65.9% of the credit portfolio as of 1 January 2026. A structured review of public disclosure finds uneven institutionalisation, with strategy and personnel commitments far outweighing independent validation and financial-impact monitoring. An explicitly simulated illustrative panel exercise demonstrates how CAGMI could be linked econometrically to bank-level risk and performance outcomes once internal data become available, and the paper closes with policy recommendations for the Central Bank of Uzbekistan and for other digitally and AI-transforming emerging-market banking systems.

Keywords: artificial intelligence governance; systemically important banks; model risk management; AI maturity model; explainable AI; credit risk; financial stability

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1. Introduction

Between 2017 and 2026, artificial intelligence in banking moved from isolated pilots — fraud detection, chatbots, minor scorecard adjustments — into a technology layer embedded beneath core lending, investment, and risk-management operations. The Financial Stability Board's (FSB) 2017 stocktake found banks still experimenting with AI/ML use cases [1]; by 2024 the FSB reported that generative and predictive AI were already embedded in credit assessment, trading, and compliance across most member jurisdictions, at the cost of growing third-party reliance, model risk, and system-wide cybersecurity exposure [2]. A 2025 FSB monitoring update found these vulnerabilities deepening rather than stabilising, driven by consolidation among a small number of external AI-model and cloud providers [3].

For a domestic systemically important bank (D-SIB) — an institution whose distress would have serious consequences for the financial system regardless of what happens to the institution itself — this shift matters more than for an ordinary bank. The regulatory logic that already requires higher loss-absorbing capital for D-SIBs has not been extended, in any comparably codified way, to the governance of the AI models such banks increasingly rely on. A defective or poorly monitored credit-scoring model at a D-SIB does not only threaten its own loan book; it can propagate a correlated, hard-to-detect error across a large share of system assets[4-6].

Two adjacent bodies of guidance leave this gap unfilled. Technology-oriented AI-maturity models assess an organisation's strategy, data, technology, talent, and governance without reference to prudential consequences. Prudentially oriented frameworks — the Federal Reserve/OCC's SR 11-7 model-risk guidance, the NIST AI Risk Management Framework [7], ISO/IEC 42001 [8], and the EU AI Act, which designates creditworthiness-scoring systems "high-risk" — describe what good governance looks like but do not generate a comparable score, nor embed a non-compensable constraint preventing a bank from claiming maturity it has not earned where it matters financially.

This paper addresses that gap by introducing the Composite AI Governance Maturity Index (CAGMI) and applying it, as a documentary and illustrative exercise, to Uzbekistan's seven SIBs. Three research questions organise the analysis. RQ1: which organisational-governance dimensions should a maturity index for AI in SIBs include, such that a high score credibly signals loss-containment capability rather than general digital-transformation activity? RQ2: how uniformly institutionalised is AI-governance practice among Uzbekistan's seven SIBs based on currently disclosed public evidence, and where is the disclosure gap largest? RQ3: once a full round of internal data collection is available, how would such an index be linked econometrically to bank-level risk and performance outcomes, and what does a calibrated illustration of that strategy suggest about the plausible direction and magnitude of the relationship?

The paper's main contribution is methodological: an index of eight governance blocks and thirty-two threshold-scored indicators, with explicit normalisation rules, a non-compensability ("red-line") mechanism, and an evidence-sufficiency coefficient distinguishing a documented finding from an unverifiable claim, extending the author's earlier doctoral methodology [9-10]. Its second contribution is empirical: the first structured comparative review of AI-governance disclosure across all seven Uzbek SIBs, together with a transparently labelled simulated panel exercise showing how the index could be linked to asset quality and profitability once real internal panel data exist. Section 2 reviews the relevant literature; Section 3 outlines the institutional context; Section 4 presents the CAGMI framework; Section 5 describes data and empirical strategy; Section 6 reports the illustrative econometric exercise; Section 7 discusses the results; Section 8 offers policy recommendations and conclusions[11].

Beyond the FSB's system-level assessments, the U.S. Financial Stability Oversight Council first flagged AI risk in its 2023 annual report, citing cybersecurity, explainability, and consumer-compliance channels, a conclusion echoed by a U.S. Congressional Research Service review tying AI/ML adoption to data availability and institutional governance capacity [12]. Together these sources establish two propositions that motivate this paper: financial-stability risk from AI in banks stems from deployment outpacing institutional capacity to validate, monitor, and, where necessary, terminate a model; and the governance problem is a property of the institution, not of the model in isolation — precisely what an institution-level maturity index should capture.

Before "AI governance" became common usage, bank supervisors already had a model-risk framework: SR 11-7 requires disciplined model development, independent validation, and lifecycle performance monitoring proportionate to an

institution's size and complexity, and defines "model" broadly enough to cover machine learning without modification. AI-specific frameworks translate the same logic: the NIST AI RMF organises risk management into Govern, Map, Measure, and Manage functions; ISO/IEC 42001 is the first AI management-system standard, covering risk assessment, lifecycle management, and third-party oversight; and the EU AI Act designates creditworthiness-scoring systems "high-risk," imposing data-governance, bias-testing, documentation, and human-oversight requirements on providers and operators. None of these, individually, produces a comparable score or a non-compensable constraint; it is the Basel Committee's D-SIB framework — holding that systemic importance justifies a stricter, non-proportional standard — that supplies the missing logic, which CAGMI extends to the domain of AI governance[13].

A mature explainable-AI (XAI) literature addresses model-level transparency: SHAP and LIME remain the dominant tools for decomposing individual predictions and are the two most widely used explainability techniques in the credit-risk literature [14]. Applications to real-world Norwegian, UK, and SME credit data find that explainable ensemble methods can match or exceed benchmark predictive performance while remaining auditable to supervisors and loan officers, and recent work extends explainable architectures to gradient-boosted ensembles — XGBoost, LightGBM, random forests — combined with SHAP and LIME. This literature, however, rarely aggregates model-level explainability into an institution-wide assessment of lifecycle governance, and the organisational AI-maturity research that does aggregate such assessments rarely connects them to concrete financial metrics such as probability of default, expected credit loss, or capital adequacy[15].

Algorithmic-fairness research is directly relevant to lending: bias can originate in data, algorithms, or feedback loops, and both U.S. enforcement practice and Article 10 of the EU AI Act treat bias-testing as a compliance requirement — which is why CAGMI embeds fairness testing as a financial and ethical governance metric. General AI-maturity frameworks — most following a five-level strategy/data/technology/process/talent/governance architecture, including Gartner's and IBM's industry models — are domain-general and were not designed to connect a maturity score to prudential outcomes. CAGMI shares their aggregation logic but differs by weighting blocks according to relevance to loss containment and by applying non-compensable red-line restrictions[16-20].

Geographically, IMF and BIS research documents both the promise and the limits of fintech-driven financial inclusion in emerging and developing markets, including Central Asia, where access constraints for small and medium-sized firms remain largely institutional rather than technological. Uzbekistan's own fintech sector has grown quickly in this environment: licensed fintech entities rose from 24 in 2018 to 103 by September 2025, with a national strategy targeting 200 firms and USD 1 billion in fintech investment by 2030, and the Central Bank's mandate was extended in December 2025 to include fintech development. Three gaps emerge from this review. First, the literature on AI and financial stability recognises governance and model risk as major concerns but offers no instrument for sizing that gap at the level of an individual firm. Second, existing regulatory frameworks define good governance without aggregating compliance into a single, comparable, non-compensable score. Third, the general AI-maturity literature supplies aggregation methodology but applies it to organisational best practice in general rather than to the financial parameters that determine the systemic materiality of a governance gap. The CAGMI framework introduced in Section 4, and applied to Uzbekistan's seven SIBs, addresses this triangle of gaps[21-25].

2. Materials and Methods

This study follows a three-part, mixed-methods design. First, it constructs a

composite governance index (CAGMI) from first principles, specifying its blocks, indicators, weights, normalisation rule, and non-compensable restrictions. Second, it applies a structured documentary content-analysis protocol to the seven SIBs' public disclosures, mapping each disclosed practice onto the index's eight blocks. Third, it specifies the econometric strategy through which a completed CAGMI score would ultimately be linked to bank-level outcomes, and, because the internal panel required for that estimation does not yet exist, demonstrates the strategy on a transparently simulated, calibrated dataset. Each component is described in turn below.

3. Result and Discussion

Institutional context: uzbekistan's banking sector and its systemically important banks

Uzbekistan's Central Bank designated seven systemically important banks for 2026: the National Bank for Foreign Economic Activity (NBU), Agrobank, Uzpromstroybank, Xalq Banki, Ipoteka-Bank, Kapitalbank, and Asakabank [10]. As of 1 January 2026 these banks held 577.03 trillion soums in assets and 398.24 trillion soums in loans — 62.4% of banking-sector assets and 65.9% of total credit [10] — a concentration meaning that a shared data, model, or vendor failure (a common external credit-bureau feed or cloud-based scoring engine) could acquire systemic reach before any single bank detects it[26].

The system is digitising quickly: digital financial-services penetration rose from 76.6% in 2021 to 94.2% in the most recent period, and the volume of financial services provided reached 171.9 trillion soums in 2025, up 24.6% year-on-year. Expert estimates cited in the underlying methodology suggest fuller AI adoption could raise bank revenue by roughly 20%, service volumes by roughly 30%, and reduce risk by roughly 15%, though these remain estimates rather than measured outcomes [10]; for comparison, a 2022 UK FCA/Bank of England survey found that 75% of regulated financial firms had already adopted AI, yet only 46% reported no material implementation difficulties — evidence that adoption is outrunning governance internationally, not only in Uzbekistan[27-29].

The regulatory framework has moved to keep pace. Presidential resolutions adopted in 2026 mandated the Central Bank to link AI model and data quality to expected credit loss, non-performing loans, risk-adjusted profitability, and capital adequacy at the seven SIBs. In December 2025 the Central Bank's mandate was extended to include fintech development, including a dedicated Fintech Office and national fintech commission, and the 2026–2030 National Strategy for Financial Technology Development, discussed with international partners including Visa, targets a national payment-switching system and open-banking infrastructure. This environment is simultaneously favourable and demanding for a maturity index: policy explicitly ties AI governance to prudential metrics rather than treating it as a purely technological or reputational matter, yet reforming seven institutions holding two-thirds of system credit, amid a fast-changing regulatory landscape and uneven baseline disclosure, is not straightforward, as Section 5 documents[30].

THE COMPOSITE AI GOVERNANCE MATURITY INDEX (CAGMI): CONCEPTUAL FRAMEWORK

An index measuring loss-containment capability rather than digital-transformation activity must meet three design requirements that the general AI-maturity literature does not uniformly impose. First, its components must be weighted by demonstrated relevance to loss containment: independent validation and data quality — not visible enthusiasm for AI — stand between a flawed model and a mispriced loan book. Second, it must resist compensability: strong cybersecurity or strategy scores should not offset a documented absence of independent validation, since these protect against different failure modes. Third, it must distinguish a documented finding from an unverifiable claim, since public

“digital transformation” statements are not evidence of the specific practices that determine whether a model failure is caught before it becomes costly[31].

CAGMI, extending the author’s doctoral methodology, satisfies these three requirements through, respectively: financially informed block weights; four non-compensable red-line restrictions; and an explicit evidence-sufficiency coefficient reported alongside every score. The index scores each SIB across eight governance blocks, each comprising four indicators on a five-point (0–4) ordinal scale — 0 indicating an absent or unconfirmed practice and 4 indicating a practice that is integrated into governance, independently verified, and improved on the basis of measured financial outcomes — for thirty-two indicators in total (Table 1)[32].

Table 1. Composite AI Governance Maturity Index (CAGMI): blocks, representative indicators, and weights

Nº	Governance block	Representative indicators (4 per block)	Weight
1	Strategy and accountability of governing bodies	Approved AI strategy; risk appetite; board/management responsibility; model and process ownership	0.12
2	Data quality, availability and traceability	Source registry; quality metrics; data lineage and transformation; control of external/alternative data	0.15
3	Model lifecycle governance	Model registry and classification; model passport; development and testing; change, suspension and decommissioning	0.15
4	Independent validation	Organisational independence of validation; pre-deployment review; back-testing and calibration; remediation tracking	0.15
5	Explainability and fairness	Explanation for specialist and client; segment-level bias testing; human review; appeal procedure	0.10
6	Cybersecurity and infrastructure resilience	Access control; vulnerability testing; cloud/vendor risk control; fallback and recovery process	0.12
7	Personnel competence	Developer/validator qualification; management training; interdisciplinary teams; knowledge transfer	0.08
8	Financial-impact monitoring	Effect on PD, expected credit loss, non-performing loans; profitability and capital; operational losses/fraud; reporting to governing bodies	0.13
	Total		1.00

The weights assign the largest combined share (45%) to data quality, model-lifecycle governance, and independent validation — the blocks most directly implicated in catching a model error before it causes loss — followed by financial-impact monitoring (0.13), which closes the loop between governance activity and measured outcomes. Strategy/accountability and cybersecurity/infrastructure receive moderate weight (0.12 each) as necessary but not sufficient preconditions; explainability/fairness (0.10) and personnel competence (0.08) receive the lowest weights as necessary complements rather than substitutes for the higher-weighted blocks. These are the author’s transparent starting weights, intended for refinement through structured expert elicitation and robustness checks under equal weighting and a $\pm 20\%$ perturbation of each weight[33].

Each block’s normalised score for bank b is computed against a fixed evaluative threshold rather than the best-performing bank in the sample, so a systemically weak sector cannot generate artificially high relative scores:

$$n(b,r) = 25 \times [\sum o(b,r,i)] / k_r \quad (1)$$

where $o(b,r,i)$ is the bank’s score (0–4) on indicator i of block r and k_r is the number of indicators in block r (four for every block), yielding a normalised block score between 0 and 100. The composite index for bank b is then:

$$CAGMI_b = \sum (r=1..8) w_r \times n(b,r), \text{ subject to } \sum w_r = 1 \quad (2)$$

Year-on-year change is tracked as $\Delta CAGMI(b,t) = CAGMI(b,t) - CAGMI(b,t-1)$ (3); a positive change signals growing organisational capability but not necessarily falling risk, since rapid model expansion can raise strategy and personnel scores while temporarily straining validation capacity, so block-level

trajectories matter as much as the composite score [10]. A system-level, asset-weighted aggregate is $SCAGMI_t = \sum (b=1..7) d(b,t) \times CAGMI(b,t)$ (4), where $d(b,t)$ is bank b 's share of the seven banks' combined assets in year t ; this reveals when a large, low-maturity bank exerts disproportionate influence on system-level resilience[34].

Because a composite sum can conceal a critical deficiency — strong scores in cybersecurity, personnel, and strategy arithmetically offsetting weak independent validation — CAGMI applies four red-line restrictions after the composite is calculated. A bank cannot be classified at the Integrated or Advanced maturity level, regardless of its numerical score, if it lacks any one of: (i) a registry of deployed AI models; (ii) independent validation of high-risk and critical models; (iii) substantive human oversight of material financial decisions; and (iv) a documented procedure for restricting, halting, and reverting a critical model to a manual fallback process. As an illustration, a hypothetical bank scoring 75, 70, 60, 55, 50, 80, 65, and 45 on the eight blocks in Table 1's order would obtain a composite score of 62.4, but if it cannot document a model-halting procedure its classification is capped at "Managed" regardless of the arithmetic score. Advanced status additionally requires every block to score at least 70, with the four highest-weighted blocks — data quality, lifecycle governance, independent validation, and financial-impact monitoring — each at least 80[35-37].

Table 2. CAGMI maturity scale and non-compensable restriction conditions

CAGMI range	Level	Characterisation	Additional condition
0–19.9	Initial	Isolated experiments; no unified governance	Critical models must not run autonomously
20–39.9	Fragmented	Separate documents and units; processes not linked	Full model inventory mandatory
40–59.9	Managed	Core processes documented and regularly controlled	High-risk models permitted only under independent review
60–79.9	Integrated	AI governance linked to risk appetite, portfolio and financial indicators	All four red-line criteria satisfied (Section 4.4)
80–100	Advanced	Continuous improvement, stress-testing, system-level assessment	Every block ≥ 70 ; the four highest-weighted blocks ≥ 80

A complete CAGMI assessment requires internal evidence rarely available from public disclosure alone: approved AI strategy documents and governance-body minutes, the model registry and individual model passports, independent validation and back-testing reports, change and incident logs, human-review records, internal audit findings, vendor contracts, and financial reporting linking model performance to expected credit loss, non-performing loans, and capital. Because full internal access is unavailable for this paper's illustrative application, each indicator's evidence base is assigned a completeness coefficient $K_b = n^d_b / 32$ (5), where n^d_b is the number of the thirty-two indicators for bank b supported by verifiable documentary evidence rather than an unverifiable public claim. Following the underlying methodology, K_b below 0.70 is reported as preliminary, between 0.70 and 0.85 as sufficient for comparative analysis, and at or above 0.85 as highly reliable. This coefficient does not adjust the CAGMI score itself; it is reported alongside it, because an unconfirmed indicator may reflect either a genuine absence of practice or simply a limit on the researcher's access. As Section 5 documents, every one of the seven banks' K_b in this exercise falls well below 0.70[38].

DATA AND EMPIRICAL STRATEGY

A complete CAGMI assessment requires internal supervisory or bank-level access to model registries, validation reports, and incident logs that are not publicly available. This paper therefore reports a narrower, fully transparent exercise: a structured documentary review of what each of the seven SIBs has publicly disclosed — through official websites, annual and sustainability reports,

organisational-structure announcements, and public statements — between 2024 and 2026, mapped against the eight CAGMI blocks [10]. This review does not produce a CAGMI score; it produces a public-disclosure maturity proxy (Table 3), indicating how much governance infrastructure a bank has made publicly visible, independent of whether that infrastructure exists internally[39].

Table 3. Public-disclosure AI-governance evidence review, Uzbekistan's seven SIBs (2024–2026 disclosures)

Bank	Publicly confirmed elements (documentary review)	Elements not verifiable from public disclosure
National Bank (NBU)	Digital transformation programme; remote banking services; strengthened business processes; public financial reporting	Dedicated AI strategy; model registry; independent validation; fairness testing; model-stopping procedure
Agrobank	AI projects and the “500 specialists” programme; personnel-development initiatives; cybersecurity measures; sustainability reporting	Unified model lifecycle; independent validation; disclosed financial metrics of AI use
Uzpromstroybank	Dedicated AI department; named Head of AI function; digital-bank and transformation programme	Public model registry; validation methodology; stopping thresholds; disclosed link to ECL/capital
Xalq Banki	AI laboratory established; AI solutions deployed in client service; planned investment in AI and cybersecurity	Model classification disclosure; independent verification; human-review procedure
Ipoteka-Bank	Integration of OTP banking-group standards; strengthened risk, cybersecurity and data governance; new AI/ML data centre	Local AI model registry; fairness-testing results; model-incident and financial-effect disclosure
Kapitalbank	AI and big-data use for suspicious-transaction detection; ESG and personnel reporting	Dedicated lifecycle management; independent validation; disclosed link to capital
Asakabank	Digital banking products; IT/digital-transformation competence development; internal and compliance control	Sufficient public information on AI strategy, models, validation and financial monitoring

The pattern is informative. Publicly confirmed elements cluster in strategy, personnel, and general digital-transformation domains: dedicated AI departments and named heads of AI function, AI laboratories and personnel programmes, banking-group standards integration and new AI/ML infrastructure, and AI applications in suspicious-transaction detection alongside ESG reporting. No bank's public disclosure confirms a public model registry, an independent validation methodology, documented model-stopping thresholds, or a disclosed quantitative link between AI-assisted decisions and expected credit loss, non-performing loans, or capital [10]. This does not prove such practices are absent internally, but it means that no outside supervisor, investor, or rating agency relying solely on public information can currently verify that any of the seven SIBs meets the Integrated or Advanced maturity standard of Table 2; every K_b in this exercise falls well below 0.70, so Table 3 must be read as a preliminary assessment of public-information availability, not a measured CAGMI score or a ranking of internal governance quality[40].

The documentary review answers RQ2 but not RQ3, since it does not jointly observe internal governance practice, model performance, and financial outcomes. Answering RQ3 properly requires an internal, multi-year CAGMI panel matched to reported non-performing loan ratios, capital adequacy, asset size, and return on assets, which does not yet exist and cannot honestly be approximated from public sources. This paper therefore specifies the estimation strategy precisely and demonstrates it on a transparently simulated, calibrated panel (Section 6), rather than disguising a numerical illustration as an empirical finding. The strategy to be applied once genuine panel data exist is a two-way fixed-effects model:

$$Y(b,t) = \beta_0 + \beta_1 \cdot \text{CAGMI}(b,t) + \beta_2 \cdot \ln(\text{Assets})(b,t) + \beta_3 \cdot \text{CAR}(b,t) + \beta_4 \cdot \text{NPL}(b,t) + \mu_b + \lambda_t + \varepsilon(b,t) \quad (6)$$

where $Y(b,t)$ is a bank-level performance or risk outcome, $CAGMI(b,t)$ is the composite index from equation (2), $\ln(\text{Assets})$ controls for bank size, CAR is the capital adequacy ratio, NPL is the non-performing loan ratio, μ_b are bank fixed effects, λ_t are year fixed effects absorbing system-wide shocks common to all seven banks, and $\varepsilon(b,t)$ is a bank-clustered error term. This follows standard practice for short, unbalanced financial panels [38,39]; once a longer panel and a plausibly exogenous CAGMI instrument become available, a dynamic Arellano–Bond-type GMM estimator would be a natural robustness extension addressing the possibility that better-performing banks simply invest more in governance rather than governance causing better performance [40].

ILLUSTRATIVE ECONOMETRIC EXERCISE

The exercise in this section is a simulated numerical illustration, not an empirical finding. It uses a synthetic panel of 77 bank-year observations covering the seven SIBs over 2016–2026, calibrated to the three-phase institutional narrative documented in the underlying methodology — an initial period (2016–2019) dominated by remote-service delivery and basic automation, a middle period (2020–2023) dominated by digital transformation and risk/cybersecurity investment, and an institutionalisation period (2024–2026) marked by dedicated AI units [10] — with capital adequacy, non-performing loan, and return-on-asset series drawn from realistic but simulated ranges rather than actual bank disclosures. Every number in this section demonstrates how the specification in equation (6) behaves, not what Uzbekistan's SIBs have actually achieved.

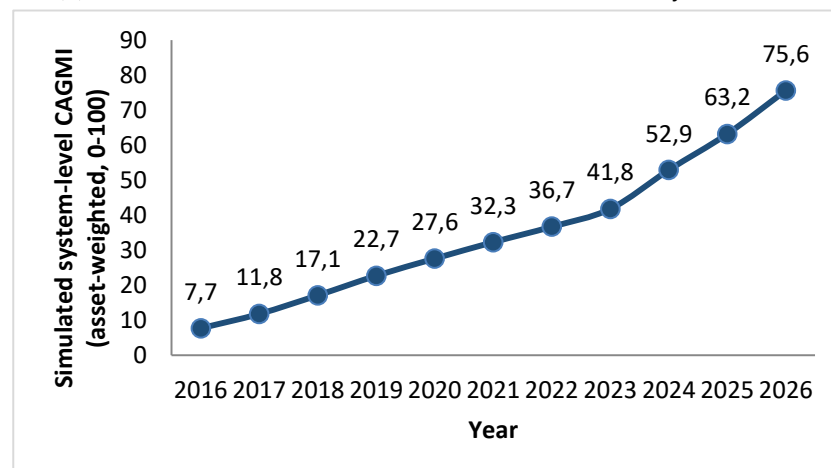


Figure 1. Simulated system-level AI governance maturity trajectory, Uzbekistan's seven SIBs, 2016–2026 (illustrative calibration; not measured data).

The simulated, asset-weighted system-level trajectory (Figure 1) is constructed to be broadly consistent with the qualitative account in the underlying methodology: a low, fragmented starting point in the mid-2010s, gradual improvement through the transformation period, and acceleration coinciding with the 2024–2026 institutionalisation drive; it should not be read as a measured historical series.

Estimating equation (6) on the simulated panel by ordinary least squares with bank- and year-fixed effects and bank-clustered standard errors, using return on assets as the dependent variable, yields the coefficients reported in Table 4 ($N = 77$, $R^2 = 0.628$, adjusted $R^2 = 0.496$).

Variable	Coefficient	Clustered S.E.	p-value
Constant	0.6596	0.4542	0.146
CAGMI (simulated)	0.0049	0.0042	0.246
$\ln(\text{Assets})$	0.0179	0.0169	0.289
Capital adequacy ratio (%)	0.0158	0.0172	0.357
Non-performing loan ratio (%)	-0.0740	0.0172	0.000

Table 4. Illustrative fixed-effects panel estimation, simulated data ($N = 77$ bank-years, 7 banks, 2016–2026)

The CAGMI coefficient is positive but not statistically distinguishable from zero once bank size, capital adequacy, and the non-performing loan ratio are controlled for, while the non-performing-loan coefficient is negative and highly significant — by construction of the simulation's data-generating process, not as a finding about Uzbekistan's actual banks. The exercise demonstrates only that equation (6) is estimable with a realistic sample size and that a fixed-effects design can, in principle, separate a governance-maturity effect from confounding bank size and capitalisation; a genuine causal test requires the internal, multi-year CAGMI panel described in Section 5, proposed here as the natural next phase of this research programme.

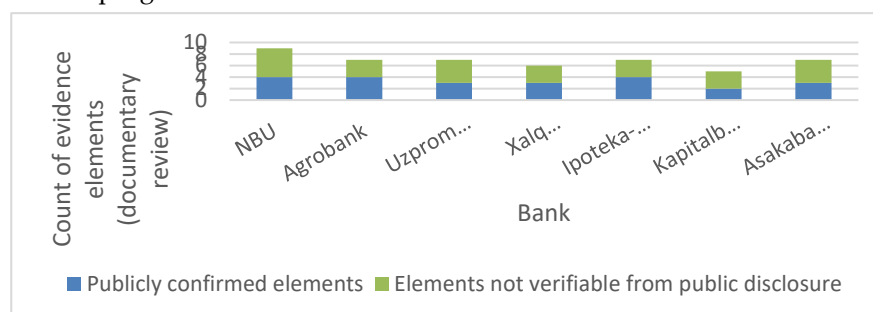


Figure 2. Public-disclosure AI-governance evidence review, Uzbekistan's seven systemically important banks (documentary review; author's compilation).

Figure 2 translates Table 3's documentary review into a simple visual count of confirmed versus unverifiable elements per bank. Unlike Figure 1, it is grounded directly in the real documentary assessment, not simulation, though it remains a public-disclosure proxy rather than a validated measure of internal governance quality, for the reasons discussed in Section 5.

5. Conclusion

Enhancing The study shows that AI governance in Uzbekistan's systemically important banks is developing in strategy, personnel, and digital transformation, while independent validation, model-stopping procedures, and financial-impact monitoring remain insufficiently documented. The proposed CAGMI provides a structured framework based on eight governance blocks and 32 indicators for assessing AI governance maturity. Future research should use internal bank data to empirically evaluate the relationship between AI governance maturity, banking risks, and financial performance.

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