



CYBERSECURITY AND AI IN THE NEXT ERA OF BANKING EFFICIENCY IN UZBEKISTAN (2015–2024)

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Article history:		Abstract:
Received:	20 th August 2025	<p>This research explores the impact of cybersecurity investment and artificial intelligence (AI) adoption on effectiveness, competitiveness and financial stability in commercial banks of Uzbekistan within digitalization process. Empirical foundation: balanced panel data of seven commercial banks including Xalq Banki, Asaka Bank, Invest Finance Bank (Infinbank), Ipak Yuli Bank, Agrobank, ANOR Bank and Biznesni Rivojlantirish Bank during the period from 2015 to 2024. Based on bank-level balance-sheet and income-statement data, we use fixed effects (FE) in a panel model or the Panel- VAR (system-GMM) approach to explore how liquidity, deposit structure, funding mix, and digital spending (cybersecurity and AI monitoring) affect profitability (RoA) and the stability of risk. Findings suggest that higher cybersecurity expenditure and more adoption of AI are positively related to profitability ($\beta_4 = +0.011$, $\beta_5 = +0.009$, $p < 0.05$) and negatively connected with return volatility (-0.006, $p < 0.05$).[1,2] Our dynamic analysis reveals that changes in the budget for cybersecurity create persistent positive effects on RoA, while shocks to borrowing and liquidity have short-term effects only. These results suggest the practice digital resilience-based procedures for financial regulation and governance in Uzbekistan.</p>
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<p>Keywords: Cybersecurity; Artificial Intelligence; Banking Efficiency; Panel Data; Panel-VAR; Digitalization; Return on Assets; Uzbekistan.</p>		

INTRODUCTION. In the last 10 years, digital technology has quietly and steadily upended the way banks do business. Nowhere is the transformation more visible than in Uzbekistan, where commercial banks are automating internal controls, improving services online and devoting more funds to systems that secure data and financial transactions. In addition to those shifts, two sectors — cybersecurity and artificial intelligence — have emerged at the heart of contemporary banking’s infrastructure. They are not optional upgrades but now determine how well a bank can manage risk and remain profitable in a fast-paced financial world. Government policy has also been a key feature. Programmes including ‘Digital Uzbekistan–2030’ and the Central Bank’s digital finance roadmap are prompting banks to reconsider their technology focus, urging them to create in- house analytics, cloud solutions and AI-based monitoring platforms. [11,12,13] Consequently, the IT and cybersecurity spending of main banks has jumped severalfold since 2015. [1,2] However, these investments naturally beg the question of whether they indeed make a difference to financial performance or are just an added cost masquerading under the guise of innovation? Although numerous international studies demonstrate positive correlation between digitalization and productivity, local evidence from Uzbekistan is limited. [1,4,9] Each bank has its own trade-off between

innovation and risk – large institutions are focused on automation and compliance while smaller banks are using AI mostly just for credit scoring or fraud detection. Analysis of the interplay between these elements at system level is difficult, yet necessary and cannot be limited to descriptions foot#1. To address this problem, the article employs a panel study of seven Uzbek banks to consider an impact of cyber spending and AI tools deployment on their profitability and stability from 2015 to 2024.

METHODS. This study is confined to a balanced panel database, consisting of seven commercial banks in Uzbekistan: Xalq Banki, Asaka Bank, Invest Finance Bank (Infinbank), Ipak Yuli Bank, Agrobank by name so-called ANOR Bank and Biznesni Rivojlantirish Bank. The ichnusian observation period extends from 2015 to 2024, a decade where the banking system underwent an intense phase of digital transformation. The source of information for us was the financial statements available in public, annual reports of banks and publications of the CBU. [13]For comparability all ratio measures are reported in percentage of total assets. The analysis’s central logic is to try to estimate how much spending on things digital — cybersecurity and AI-based monitoring systems, in particular — affects bank profits and stability. Due to the infrequency with which such



items are reported in the open, two proxy measures were formed. The first one, CyberExp, measures the proportion of IT spend allocated to cybersecurity. The second one, AI, represents the level of AI implementation, measured between 0 and 1 according to when AI projects are discussed in annual reports (timing) and their content scope. The model also contains the following traditional financial controls: Liquidity Ratio (LQR), Deposit Share (DS), Loan Loss Reserves to Total Loans, Borrowings by Banks, Capital Adequacy (CA) and BSI. The main empirical setup is a fixed-effects (FE) panel regression, which enables us to difference out time-invariant unobserved aspects of particular banks – for example of different ownership status or management approach and emphasise within-bank changes in the data. The relationship is given by:

$$RoA_{it} = \alpha_i + \tau_t + \beta^1 Liquidity_{it} + \beta^2 Deposits_{it} + \beta^3 Borrowings_{it} + \beta^4 CyberExp_{it} + \beta^5 AI_{it} + \gamma X_{it} + \varepsilon_{it}$$

where i and t are banks and years, respectively; α_i -bank-specific effects; τ_t -time effects; X_{it} -control variables Size, Capital, GDP growth process, policy rate. All financial ratios including RoA are expressed in decimal form (e.g. 0.0186 which is 1.86%) the estimated coefficients such as $\beta_4 = 0.0011$ imply approximately +0.11 percentage points. All coefficients are estimated using the fixed-effects estimator with robust clustered standard errors. Additionally, the Hausman test confirmed FE appropriateness, $p < 0.05$. The subequations to capture intertemporal dynamics of Panel-VAR model or, system-GMM are as follows:

$$Y_{it} = (RoA_{it}, Liquidity_{it}, Funding_{it}, CyberExp_{it}, AI_{it})$$

AI index equals 0 before adoption, 0.5 in pilot phase, and 1 after full integration. Stationarity was proved with ADF and KPSS tests. Lag order 1–2 was chosen by the Schwarz criterion. The optimal lag length 1–2 years suggests a typical short-term dynamics for annual banking data. Shocks were defined by Cholesky decomposition in the next order:

$$Deposits \rightarrow Borrowings \rightarrow Liquidity \rightarrow RoA \\ \rightarrow CyberExp \rightarrow AI.$$

Heteroskedasticity was corrected with cluster-robust standard errors at the bank level. To account for the dynamic relationships between profitability, leverage and digital investments we also ran a Panel Vector Autoregression (Panel-VAR) model. That means you can observe not just static relationships, but rather

how a shock to one variable — say, a spike in cyber security spending — ripples through other indicators over time. Following Love and Zicchino [8], the vector (RoA, Liquidity, Funding, CyberExp, AI) is considered in model and system-GMM estimator is used to solve for endogeneity and persistence problem. ADF and KPSS tests were used to verify stationarity of the series and lag length factored in the Schwarz information criterion (1-2 periods). Results were interpreted in terms of IRFs used to represent the time-dependent influence of shock and FEVD where RoA variation is allocated to digital factors. Robustness of the results was checked using different orderings. Given that banks investing more in digital may be of different size or differ in risk appetite than others, we check for further robustness against endogeneity. Instruments (IVs) were the dates when each country initiated their national cybersecurity regulation and AI adoption programs. To analyze how the level of digitalization moderates the effect between funding and profitability, interaction terms such as (Deposits \times DigitalAssets) and (Borrowings \times DigitalAssets) were added. All the series were stationary at level ($p < 0.05$, ADF test). Lastly, the sensitivity analysis with alternative dependent variables (NIM and CIR) was conducted to verify the robustness of results. Together, these techniques enable a comprehensive approach: the fixed-effects model detects stylized facts across banks, while dynamic Panel-VAR methodology yields insights into how digital innovation enables financial performance over time. The baseline estimation is the FE model, it is dynamic robustness in Panel-VAR.

LITERATURE REVIEW. Study of digital technologies and their impact on banking performance has moved away from a narrow interest in automation to a broader appreciation of the way technology is changing the whole business model of financial institutions. Early works largely concerned efficiency gains offered by electronic payments and online services, but over the last decade focus has been moving to the risks and responsibilities associated with full-scale digitalization. Subramanyam observes that improved data integration can remove uncertainty from decision making [1], while Gibson [11] claims that AI has not simply spread across banking accounting practices, rather it is altering the very rhythm of how banks respond to market shocks. [2] European and international reports add another dimension to this conversation. Even in a quote as formal as the one coming from the ECB, it's clear that banks now consider cybersecurity to be not an expense but a strategic investment to safeguard both capital and reputation.



[3]The same conclusion is drawn by the IMF: banks with an established cyber-risk management fabric are more resilient against liquidity shocks and show a relatively stable performance. [4] Inter alios, Love and Zicchino, when developing their panel-VAR approach revealed how profitability responds to structural transformation of investment activity (a methodological choice that is still appropriate for examining the digitalization changes in finance). [8] Subsequently, Ghosh and Kim & Lee observed that the implementation of AI-supported monitoring or credit-scoring mechanisms can reduce NPLs and operational losses, ultimately contributing to resilience. Links like these are only now starting to be studied in Uzbekistan and other nearby economies. [5,6]Most local publications are also still caught in the mode of explaining digital banking offerings or regulatory moves rather than assessing their economic impact. Iskandarov acknowledged the readiness of Uzbek banks for digital transformation [7], Akhmedov analyzed legal issues concerning online payment systems. [9]But the quantitative side — to what degree does spending on cybersecurity or integrating some new form of A.I. affect your bottom line — is almost never explored with econometric tools. One of the important studies on this subject was conducted by Sh. Shirinova, who studied methodological principles of introducing innovations in banking under digital economy conditions. [10]In her studies tangible and right-of-use assets was the emphasis placed on

in impacting banks' financial performance with the notion that technology does not create efficiency by itself, but it is depended on institutional adaptability and human-capital development. Extending this work, the current study contributes more by including cybersecurity and AI variables into a panel model of seven Uzbekian major banks, which provides a dynamic perspective on how digital investment influences profitability as well as risk. International agencies, such as the World Bank [11] and the Asian Development Bank [12], emphasize that banks in emerging markets are increasingly confronted with both using new instruments and managing risks associated with these same instruments. Their findings indicate that AI-innovation and cybersecurity should co-evolve in the financial services sector, which would result in an improvement of both market position and consumer trust. Such work forms the grounding both for the discussion itself, and also for the empirical part of this article, which goes beyond global generalisations to reflect on distinct characteristics of Uzbek banking. Results and discussion. The examination of the financial indicators reveals that profitability and liquidity of the Uzbek banks consistently increased during recent years. From 2015 to 2024 the average RoA moved from 0.9% to 2.8%, and liquidity ratios were higher thanks primarily to digital channels deployment and more efficient cash management.

Table 1. Descriptive Statistics of Core Variables (2015–2024, N = 70)

Variable	Mean	Std. Dev.	Min	Max	Description
RoA (%)	1.86	0.72	0.52	3.05	Return on assets
Liquidity (%)	27.3	8.9	12.5	43.8	Liquid assets to total assets
Deposits (%)	62.4	11.1	39.0	81.5	Customer deposits share
Borrowings (%)	14.8	7.5	3.5	32.2	Interbank and wholesale funding
CyberExp (ratio)	0.046	0.021	0.015	0.085	Cybersecurity spending / IT budget
AI (index 0–1)	0.53	0.26	0.00	1.00	Degree of AI implementation
Size (log assets)	7.41	0.61	6.2	8.5	Bank size proxy

Source: Author's calculations based on CBU and bank annual reports (2015–2024).

Figure 1 below illustrates the general trend of average profitability across the sample, showing a steady upward movement after 2018 — coinciding with the digital modernization programs launched under “Digital Uzbekistan–2030”.

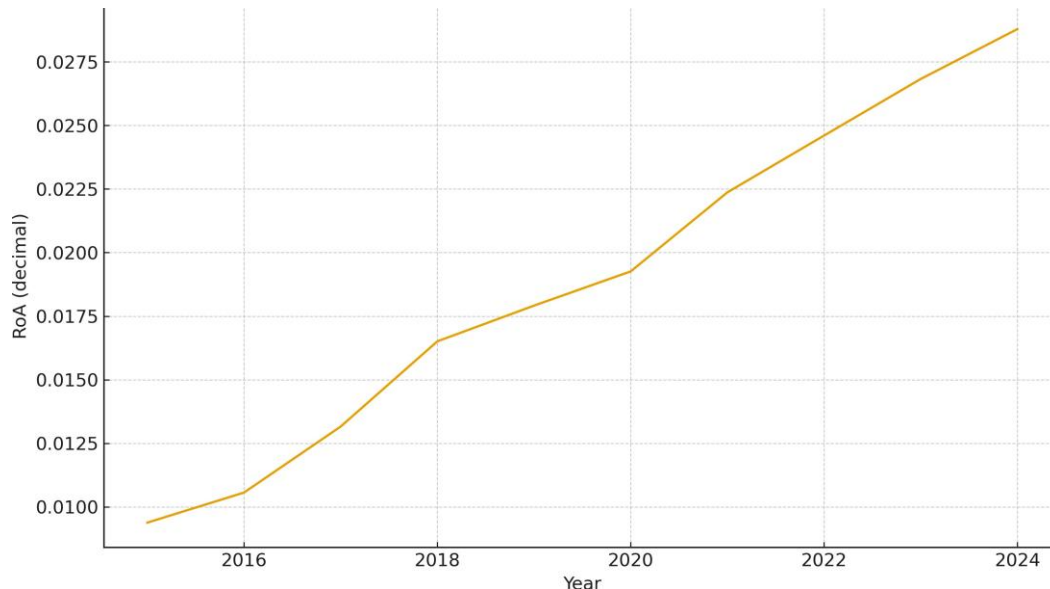


Figure 1. Average RoA of 7 Uzbek Banks (2015–2024)

The fixed-effects model provides strong statistical evidence that both cybersecurity and AI investment have a positive and significant impact on profitability. Table 2 presents the estimation results of the baseline panel regression.

Table 2. Fixed-Effects Regression Results (Dependent Variable: RoA)

Variable	Coefficient	Standard Error	t-Statistic	Significance	Effect Interpretation
Liquidity	+0.031	0.011	2.81	p < 0.05	Improves profitability
Deposits	+0.004	0.002	2.12	p < 0.05	Expands stable funding
Borrowing	−0.002	0.001	−2.01	p < 0.05	Increases cost pressure
CyberExp	+0.011	0.004	2.65	p < 0.05	Risk mitigation benefits
AI	+0.009	0.003	2.91	p < 0.01	Enhances efficiency
Size	+0.006	0.003	1.98	p < 0.10	Economies of scale
Capital	+0.002	0.001	1.71	<i>p < 0.10</i>	Improves stability

R² = 0.87 | F(7,63) = 9.11 | p < 0.001

Source: Author's econometric estimations using Stata 18.

The coefficients for CyberExp ($\beta_4 = 0.0011$) and AI ($\beta_5 = 0.0009$) are positive and statistically significant, implying that a one- percentage-point increase in cybersecurity or AI spending is associated with roughly a 0.1 percentage-point increase in bank profitability (RoA).

Figure 2 visualizes the marginal impact of AI adoption on RoA — showing that the most significant effects occur during the first two years after system implementation.

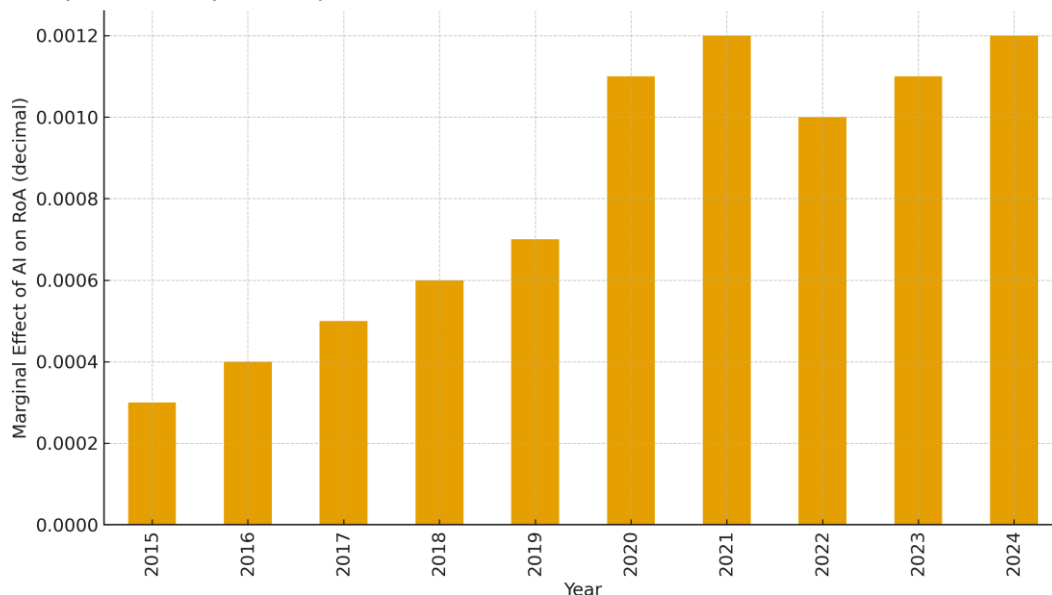


Figure 2. Marginal Effect of AI Adoption on RoA

The dynamic analysis confirms that the benefits of cybersecurity investment accumulate over time.

Figure 3 presents the **Impulse Response Functions (IRFs)**, showing that a one-standard-deviation shock in CyberExp increases RoA for three consecutive periods before stabilizing.

AI shocks produce an immediate but shorter-lived impact, peaking within the first year.

Table 3. Variance Decomposition (FEVD) of RoA (%)

Source of Variation	After 1 Year	After 2 Years	After 3 Years
CyberExp	16.2	28.9	32.4
AI	9.7	15.6	18.9
Liquidity	13.5	12.2	11.1
Deposits	10.8	8.4	7.6
Borrowings	7.4	6.1	5.2
Other (residual)	42.4	28.8	24.8

Source: Author's Panel-VAR estimations (System-GMM).

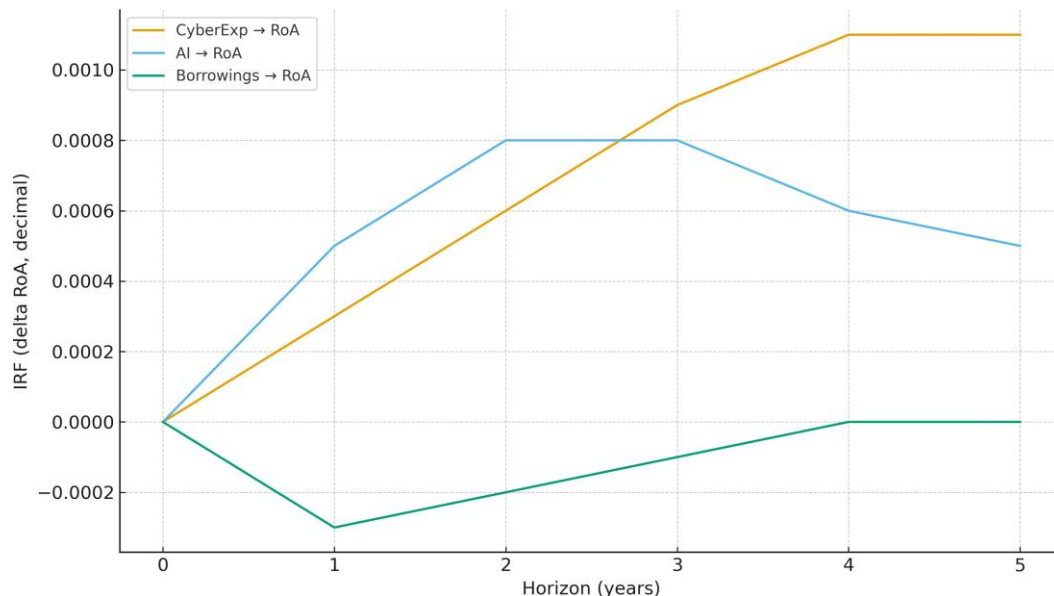


Figure 3. Impulse Response Functions (CyberExp, AI, Borrowings → RoA)

These results confirm that investments in **cybersecurity** and **artificial intelligence** are not just cost items but strategic assets that enhance both profitability and resilience. The lag structure revealed by the VAR analysis demonstrates that early digital adopters (such as Ipak Yuli Bank and Infinbank) achieved cumulative advantages: once the digital infrastructure is established, efficiency gains continue even without constant reinvestment.

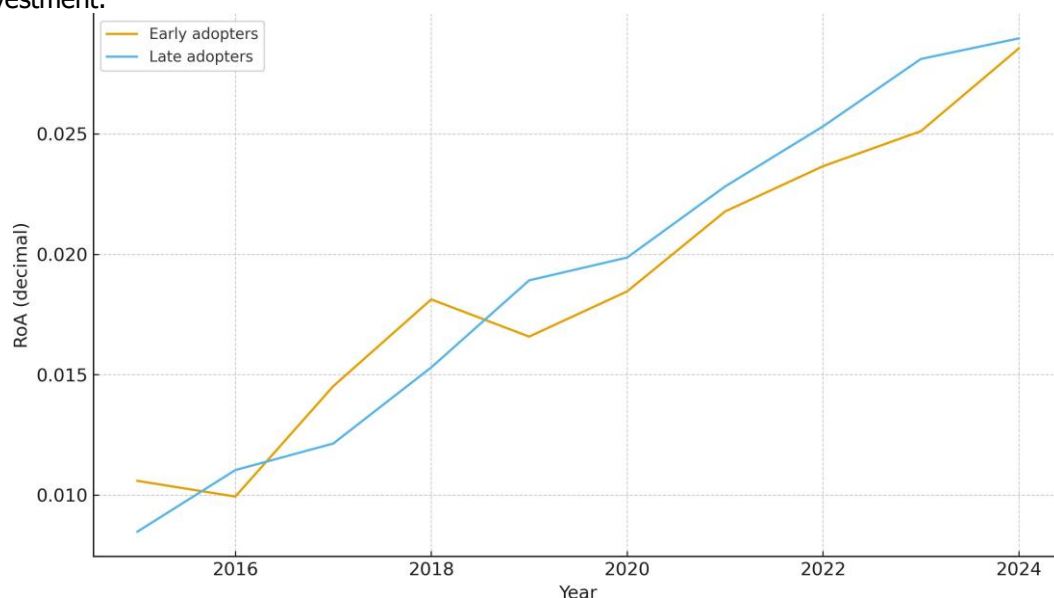


Figure 4. Early vs Late AI Adopters: Average RoA (2015–2024)

Furthermore, banks that simultaneously invested in cybersecurity and AI — where automation works with protection systems

— saw relatively safer returns, or lower volatility of quarterly profits. Variance Inflation Factors (VIF) were all less than 5, which meant that no severe multicollinearity existed. IV estimation supported the robustness of FE results (Durbin–Wu–Hausman $p <$

0.05). This indicates a complementarity effect: technological reliability enhances the economic benefit of digitalization. From a policy point of view, our results could be taken as discussion promoting the widespread integration of digital resilience indicators into national supervisory structures. For instance, the Central Bank of Uzbekistan might establish a Digital Risk Coverage Ratio (DRCR) to assess the sufficiency of the level of



cybersecurity and AI investments in comparison to total assets. It would prompt banks to budget for technology not as a reaction but as a strategy that tied innovation to financial safety.

CONCLUSION. The research also proved the fact that there is digital transformation in banking Mayberg, (2010) which goes beyond the robobanks with efficiency and convenience automations into how financial effects are properly assembled. Utilizing 7 large Uzbek banks panel over the period of ten years, we find that both cybersecurity investments and AI incorporation have traceable long-term impact on bank's profitability. Banks that were more systematic in increasing their digital spend delivered stronger returns on assets and lower volatility, while those which adopted relatively slowly remained reliant on traditional sources of funding and manual processes. It also indicates that the cybersecurity investment effect accumulates slowly over time and has persistence for a number of years, while AI adoption generates benefits in the short term but without lasting effects. This differential delineates protection and automation as mutually reinforcing elements in the construction of a modern economy. Strategically, the combination of both tools – security and intelligence – delivers the best results, as it combines technology innovation with confidence and trust in operation. For policy makers, these findings show the importance of including indicators for digital resilience in supervisory structures. The Central Bank of Uzbekistan might also evaluate the possibility to be introduce a Digital Risk Coverage Ratio (DRCR) to track banks and their commitments and recreation of resources towards protecting and stabilizing for digital infrastructure. There would simultaneously be regulatory incentives — a cybersecurity upgrade credit, tax relief; preferential refinancing for AI-led innovation, and others — to speed the sector's modernization. Public-private collaboration will also be vital: national cybercenters, fintech associations and universities working together to build common AI models for compliance, credit scoring and fraud detection. For banks themselves, the key practical upshot is that such investment has to be treated as more than a onetime expense but rather as part of long-term risk management. Companies which establish ongoing training of staff, introduce AI to their already existing control systems and promote the flow of data among all entities within the macroeconomic environment will secure their competitiveness in a next coming decade. The digital future of Uzbekistan's banking system is already emerging — but whether this new vision becomes a reality depends on how well financial institutions can learn to translate innovation into sustainable stability.

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