HSR (LONDON),
HOUGHTON STREET REVIEW JOURNAL
ISSN: 2058-5519|Impact factor-15.9
http://houghtonstreetreview.com/index.php/hsr

ECONOMIC EFFICIENCY AND SECURITY ISSUES IN THE IMPLEMENTATION OF ARTIFICIAL INTELLIGENCE TECHNOLOGIES IN COMMERCIAL BANKS: PROBLEMS AND SOLUTIONS

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Abstract. The accelerated adoption of artificial intelligence (AI) technologies in commercial banking has reshaped the operational logic, risk architecture, and competitive boundaries of financial institutions worldwide. This article examines the dual nature of AI integration—its economic efficiency dividends and its emerging security vulnerabilities—through a synthesis of recent empirical evidence from developed and developing markets, with particular attention to the case of the Republic of Uzbekistan. Drawing on data from international financial supervisors, peer-reviewed studies, and recent industry reports, the paper finds that AI deployment generates measurable gains in operational productivity, credit risk assessment accuracy, customer-service automation, and cross-channel personalization, while simultaneously introducing previously unknown risks linked to model opacity, adversarial attacks, deepfake-enabled fraud, third-party dependencies, and data-governance failures. The analysis proposes a four-tier framework—Data integrity, Algorithmic accountability, Operational resilience, and Supervisory convergence (DAOS)—as a structured response to the trade-offs banks face. Empirical illustrations from Uzbek commercial banks demonstrate that local AI deployment improves credit-scoring accuracy by 14–16 percentage points relative to traditional models, but remains constrained by talent shortages, fragmented data ecosystems, and incomplete regulatory infrastructure. The paper concludes that economic efficiency and security are not competing objectives but complementary outcomes that depend on the institutional maturity of governance frameworks, the integration of cybersecurity into AI lifecycle management, and the alignment of national supervisory practice with emerging international standards.

Keywords: artificial intelligence, commercial banks, economic efficiency, cybersecurity, fraud detection, banking governance, digital transformation, Uzbekistan, financial regulation.

The transformation of commercial banking under the influence of artificial intelligence (AI) has reached a stage where the strategic question is no longer whether to deploy AI, but how to govern it. Within a relatively short period, machine learning, natural language processing, and generative AI have moved from peripheral experimentation to embedded operational use across credit underwriting, anti-money-laundering monitoring, customer interaction, treasury operations, and cybersecurity. Industry observers report that a substantial majority of large banking institutions globally now maintain dedicated AI investment plans, while mid-sized and emerging-market banks are accelerating adoption at a comparable pace. The economic case for AI adoption rests on a combination of cost reduction, revenue uplift, and risk mitigation. Empirical work conducted on Chinese commercial banks demonstrates that AI adoption is positively associated with profitability through three reinforcing mechanisms: lower labour costs, diversification of income, and the expansion of mobile banking. Studies covering developed economies similarly find a positive association between AI investment and the efficiency of financial institutions. Yet recent patent-based analyses of large U.S. commercial banks suggest that the realized benefits of AI innovation depend on firm-wide adoption

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maturity, with short-run profitability often deteriorating when AI projects are deployed in isolation from broader organizational change. The security dimension is increasingly inseparable from the efficiency dimension. The Federal Reserve, the U.S. Department of the Treasury, the European Banking Authority, and other supervisory bodies have warned that AI tools are now used by both defenders and attackers, generating an escalating arms race in fraud, social engineering, and infrastructure compromise. Recent industry research found that approximately sixteen percent of breaches involved AI-driven elements, and the overwhelming majority of organizations that experienced AI-related incidents lacked basic AI access controls.

The objective of this article is to provide a structured analysis of the economic efficiency and security issues that arise when commercial banks implement AI technologies, identify the principal problems that emerge along both dimensions, and propose practical solutions adapted to both advanced and transition-economy contexts. The study contributes to the literature in three ways. First, it integrates evidence from developed and emerging markets on the simultaneous economic and security impacts of AI in banking. Second, it formalizes a four-tier governance framework—Data integrity, Algorithmic accountability, Operational resilience, and Supervisory convergence (DAOS)—that links efficiency outcomes to security controls. Third, it grounds the analysis in the specific institutional context of Uzbekistan to support evidence-based policy guidance for similar transition economies. The remainder of the article is organized as follows. Section 2 reviews the relevant literature. Section 3 describes the methodology. Section 4 presents the analysis of economic efficiency. Section 5 examines security challenges. Section 6 discusses problems and proposes solutions, including the DAOS framework. Section 7 concludes.

The literature on AI in banking spans four broad strands: (i) productivity and profitability effects; (ii) credit risk and decision quality; (iii) cybersecurity and fraud; and (iv) governance and regulation. In the productivity strand, empirical analysis of panel data from 430 Chinese commercial banks (2007–2022) concluded that AI adoption raises bank profitability primarily through cost reduction, income diversification, and the development of mobile banking channels. A cross-country study covering 24 jurisdictions identified a positive relationship between private AI investment and the efficiency of financial institutions. By contrast, a patent-based study of 31 large U.S. commercial banks (2015–2024) reported that AI innovation can improve asset quality but also raise short-run operating costs and depress profitability when adoption is partial; the adverse association is mitigated when firm-wide AI adoption follows the initial innovation phase. This dispersion of findings indicates that the relationship between AI and economic performance is conditional on organizational maturity, scale of deployment, and complementarity with human capital. The credit-risk literature documents AI's contribution to default prediction, scoring accuracy, and early-warning systems. Foundational contributions established the predictive superiority of machine-learning credit-scoring models over linear-regression and traditional scorecard approaches. More recent work in the post-2020 period has applied deep learning, gradient boosting, and ensemble methods to retail and SME credit, with reported accuracy improvements of 10–20 percentage points relative to logistic-regression benchmarks. Studies set in Uzbekistan find AI-enabled credit assessment in commercial banks reaching 84.7 percent accuracy, an improvement of 14–16 percentage points over standard scoring approaches.

The cybersecurity strand has expanded rapidly with the emergence of generative AI. A recent mixed-methods study identified four recurring socio-technical failure modes that hinder trustworthy AI-driven cyber threat intelligence in finance: shadow use of public AI tools, license-first deployment without operational integration, attacker-perception gaps, and the absence of security around the AI

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models themselves. The Federal Reserve has warned that bank identity-verification systems, particularly those relying on voice biometrics, are increasingly vulnerable to deepfake attacks, while industry surveys indicate that more than ten percent of companies experienced deepfake fraud attempts. The governance strand emphasizes the convergence of model risk management and information security. The U.S. Treasury report Managing Artificial Intelligence-Specific Cybersecurity Risks in the Financial Services Sector and subsequent interagency guidance have established AI cybersecurity as a sector-wide supervisory priority. The European Union Digital Operational Resilience Act (DORA), Bank for International Settlements (BIS) Papers No. 126, and OECD policy work on AI in the financial sector of developing economies converge on a common message: AI deployment must be matched by auditable governance, robust third-party risk management, and continuous testing. Despite this expanding body of work, several gaps remain. First, the literature treats efficiency and security largely in separate empirical traditions, while in practice these dimensions are mutually constitutive—AI failures impose efficiency costs, and inefficient governance produces security vulnerabilities. Second, transition-economy evidence is scarce relative to studies of OECD jurisdictions. Third, integrative frameworks that translate empirical findings into managerial and supervisory practice remain underdeveloped. The present article addresses these gaps.

This article adopts a qualitative-analytical approach combining systematic synthesis, comparative institutional analysis, and the construction of a normative governance framework. The methodology proceeded in four stages. In the first stage, peer-reviewed publications, supervisory reports, central-bank statements, and industry research issued between 2020 and 2026 were reviewed. Sources were drawn from Scopus-indexed journals; the websites of the Federal Reserve, the U.S. Department of the Treasury, the Bank for International Settlements, the European Banking Authority, the OECD, and the International Monetary Fund; and the official communications of the Central Bank of the Republic of Uzbekistan. Industry sources included IBM, McKinsey, Gartner, Datos Insights, and major commercial-banking groups operating in the relevant markets.

In the second stage, evidence on economic efficiency was extracted and organized along three dimensions: operational productivity, profitability and cost structure, and revenue and customer-experience effects. Indicators included reported changes in operating expenses, net interest margin, return on equity, customer-acquisition cost, fraud-loss ratios, and process cycle times. In the third stage, security risks were classified using a layered taxonomy: technical risks intrinsic to AI systems (data poisoning, adversarial inputs, model drift, hallucinations); operational risks from deployment (third-party dependencies, shadow AI, insufficient monitoring); and external risks from adversarial use (deepfakes, AI-enabled phishing, synthetic identities, automated reconnaissance). In the fourth stage, an integrative framework was developed by mapping each efficiency mechanism to the security controls required to preserve its value. The framework, designated DAOS (Data integrity, Algorithmic accountability, Operational resilience, Supervisory convergence), is presented in Section 6. Throughout, the case of the Republic of Uzbekistan is used as an illustrative transition-economy reference, supported by data from the Central Bank of Uzbekistan and recent academic analyses of the Uzbek banking ecosystem.

The economic case for AI in commercial banking can be decomposed into four channels: cost reduction, revenue uplift, risk mitigation, and infrastructural modernization. Each channel produces measurable financial effects, and each interacts with security considerations addressed in Section 5. The most immediate economic effect of AI adoption is the automation of high-volume, rule-bound processes. Customer-service handling, payment reminders, document-based onboarding, internal compliance reviews, and routine reconciliation are areas where machine-learning models, large

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language models, and robotic process automation displace manual work or substantially reduce processing time. Recent industry reporting indicates that AI agents at TBC Uzbekistan handled more than ninety percent of early-stage payment-reminder calls in the first half of 2025, up from roughly forty percent at the beginning of the year, while preserving customer-experience scores comparable to human-operated channels. JPMorgan Chase, the largest U.S. bank by assets, reported full-year 2025 net income of 57.5 billion U.S. dollars with return on tangible common equity of twenty percent, and announced technology spending of approximately 19.8 billion U.S. dollars for 2026 (a year-over-year increase of ten percent), with AI use cases extending across customer service, fraud analytics, and software development.

AI shifts banks from generic to hyper-personalized pricing, product recommendations, and channel orchestration. Empirical evidence from Chinese banks indicates that AI-enabled mobile banking drives non-interest income growth by lowering acquisition costs and increasing per-customer product penetration. In Central Asia, TBC Uzbekistan has reached 22 million registered users—more than half of the country's population—and reports that bilingual AI agents trained on proprietary Uzbek-language data outperform off-the-shelf multilingual models, translating into measurable improvements in conversion rates. These results are consistent with the broader observation that AI's revenue effects are strongest where models are tuned to local linguistic and cultural specifics. AI's contribution to credit risk, market risk, and operational-risk management is well documented. Modern gradient-boosted and deep-learning models capture non-linear relationships and high-dimensional interactions that conventional scorecards miss. In Uzbek commercial banks, AI-driven credit scoring has reached 84.7 percent accuracy, exceeding traditional models by 14–16 percentage points. In anti-money-laundering and fraud detection, real-time scoring of transactions allows banks to reduce false positives, accelerate alert triage, and lower investigative cost per case. AI adoption is also a vector for broader IT modernization, since high-quality machine-learning pipelines require unified data lakes, cloud-native compute, and standardized model-serving infrastructure. The accelerated digitization of Uzbekistan's banking system reflects this dynamic: between 2018 and 2023, the number of electronic transactions increased twelvefold and their aggregate value ninefold, supported by remote-identification systems, QR-payment infrastructure, and the integration of digital identity (OneID).

Table 1 summarizes representative quantitative indicators of the economic effects of AI in commercial banking.

Table 1.

Selected economic indicators of AI implementation in commercial banks

Indicator	Reported value
AI investment in financial services (2023)	≈ USD 35 billion total, of which ≈ USD 21 billion in banking
Banks with > USD 100 billion in assets fully integrating AI by 2025	≈ 75 %
Credit-risk assessment accuracy in AI-enabled Uzbek banks	84.7 % (14–16 pp higher than traditional scoring)
Share of early-stage payment-reminder calls	> 90 % (up from ≈ 40 % at start of

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handled by AI (TBC Uzbekistan, H1 2025)	year)
Increase in number of electronic transactions in Uzbekistan (2018–2023)	× 12
Increase in value of electronic transactions in Uzbekistan (2018–2023)	× 9
JPMorgan Chase technology spending (2026, planned)	≈ USD 19.8 billion (+10 % YoY)

The aggregate evidence suggests that the economic effects of AI in commercial banking are substantial but conditional. Returns accrue to institutions that pair AI adoption with organizational redesign, data-infrastructure investment, talent development, and customer-trust management. Where these complementary investments are absent, AI projects often deliver disappointing returns and may even raise short-run costs. The security dimension of AI deployment in banking has evolved from a technical concern into a systemic risk topic. This section organizes the principal threats into three categories: AI-specific technical vulnerabilities, operational and governance risks, and external adversarial use of AI. Machine-learning models introduce novel attack surfaces. Data poisoning attacks corrupt training data to nudge model outputs in attacker-preferred directions; adversarial-input attacks craft seemingly benign requests that elicit unsafe behavior; model-drift exploitation takes advantage of the slow degradation of model performance against changing data distributions. Generative AI models additionally suffer from hallucination—the generation of fluent but factually incorrect content—and from prompt-injection attacks that can subvert automated decision pipelines. The Bank for International Settlements and several national supervisors have stressed that financial institutions must maintain continuous monitoring, robust validation, and periodic stress-testing of AI models, in addition to traditional model risk management.

Operational risks arise where AI is deployed without commensurate controls. Four specific failure modes have been documented in finance-focused empirical work: shadow use of public AI tools by employees, with sensitive data leaving institutional perimeters; license-first deployment, in which AI tools are procured without integration into operational and audit pipelines; attacker-perception gaps, in which adversarial threat models are insufficiently incorporated into AI design; and the absence of security controls around the AI models themselves, including limited monitoring, robustness evaluation, and audit-ready evidence. Third-party dependencies further amplify risk: as the U.S. interagency third-party guidance (2023) emphasizes, a banking organization's use of third parties does not diminish its responsibility for safe and sound operations. The most rapidly evolving security concern is the use of AI by attackers themselves. Industry research indicates that approximately sixteen percent of recent data breaches involved AI-driven elements, with the overwhelming majority of organizations that experienced AI-related incidents lacking proper AI access controls. Comprehensive surveys document a tenfold rise in AI-generated fraudulent reviews, a projected ninefold increase in deepfake fraud relative to 2023 levels, and a more than fourfold increase in AI-enabled scam reports. Federal Reserve Vice Chair for Supervision Michael S. Barr has highlighted the vulnerability of voice-based identity verification to generative-AI-enabled spoofing, particularly given the post-pandemic normalization of remote channels.

Table 2 maps these threat categories to representative incident types and to the principal control domains that should be activated in response.

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Table 2.

Threat-control mapping for AI-enabled banking

Threat category	Representative attack types	Primary control domains
AI-specific technical vulnerabilities	Data poisoning; adversarial inputs; prompt injection; hallucination; model drift	Model risk management; data governance; continuous validation
Operational and governance risks	Shadow AI; third-party concentration; weak monitoring; insufficient audit evidence	AI-system inventory; vendor risk management; internal audit; MLOps
External adversarial use of AI	Deepfakes; AI-generated phishing; synthetic-identity fraud; AI-assisted malware	Identity verification; fraud analytics; cyber threat intelligence; customer education

The security picture that emerges is not one of catastrophic singular events, but of the silent multiplication of small failures at machine speed. Where controls are weak, automation can replicate the same error at high volume before human supervisors detect the pattern.

The preceding analysis exposes a coherent set of problems and admits a structured response. This section first summarizes the principal problems and then introduces the DAOS framework as a concise expression of the response. Six problems recur across the literature and across the institutional contexts examined. The first is the efficiency–security trade-off illusion: institutions often treat security investment as a cost that reduces efficiency, ignoring the larger losses that materialize when AI fails or is exploited. The second is the talent gap: the shortage of personnel skilled in both machine learning and financial-sector risk management is acute in transition economies, including Uzbekistan, where ecosystem-readiness assessments emphasize the constraints created by AI talent shortages and uneven infrastructure. The third is the data-quality bottleneck: AI performance is bounded by the quality, completeness, and representativeness of input data, and many banks operate with fragmented legacy systems. The fourth is the fragmented-governance problem: fraud, compliance, model risk, and information security typically reside in separate organizational silos with inconsistent policies and overlapping mandates. The fifth is the third-party concentration problem: AI adoption typically increases reliance on a small number of cloud providers, foundation-model vendors, and specialized fintech partners, raising contagion risk. The sixth is the regulatory lag: supervisory frameworks evolve more slowly than the technology, leaving gaps that adversaries exploit.

The DAOS framework offers a four-tier response in which each tier addresses a distinct class of problems while preserving interoperability with the others. The first tier, Data integrity, requires banks to treat training and inference data as a regulated asset class. Practical measures include data-lineage tracking, bias and quality testing, the segregation of personal data, and the introduction of privacy-preserving techniques such as federated learning and differential privacy. Without robust data integrity, model performance is unstable and audit defensibility is impossible. The second tier, Algorithmic accountability, extends classical model risk management to AI-specific risks. Each model should be inventoried, classified by risk tier, validated independently, monitored in production for drift, and

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stress-tested against adversarial inputs. Generative-AI deployments require additional controls for hallucination, prompt injection, and unauthorized capability expansion.

The third tier, Operational resilience, embeds AI into the bank's broader operational-risk and business-continuity architecture. This tier covers incident-response playbooks for AI failures, fall-back human-in-the-loop processes for high-impact decisions, role-based access to AI tooling, the elimination of shadow AI through provisioning of compliant alternatives, and the integration of fraud analytics with security operations. The fourth tier, Supervisory convergence, addresses the regulatory environment. Banks should pre-emptively align internal practice with emerging international standards (DORA in the European Union, Treasury and FFIEC guidance in the United States, BIS principles, OECD frameworks for developing economies) and engage constructively with their national supervisors. In transition economies, this tier is also a vehicle for institutional learning: domestic regulators, central banks, and bankers' associations can pool resources to develop national AI-banking standards rather than each institution reinventing them in isolation. The DAOS framework is intentionally cumulative: deficiencies in lower tiers undermine higher tiers. A bank that lacks data integrity cannot run effective algorithmic accountability; a bank with fragmented operational resilience cannot benefit from supervisory convergence even if it formally adopts the relevant standards.

For commercial banks in transition economies, four recommendations follow from the foregoing analysis. First, AI investment should be paired with explicit governance budgets, on the order of fifteen to twenty percent of the AI program cost, allocated to model risk, data engineering, and security controls. Without this earmark, governance lags adoption and security debt accumulates. Second, national regulators should publish AI-specific supervisory expectations covering model inventories, validation, third-party risk, and incident reporting. The 2024 Strategy for the Development of Artificial Intelligence Technologies until 2030 in Uzbekistan provides a strategic anchor [25], but banking-specific implementing rules are still maturing and would benefit from harmonization with BIS, OECD, and EU practice. Third, sector-wide initiatives should address the talent gap. University–bank partnerships, joint training programs, and the development of curricula combining quantitative finance, machine learning, and information security can compress the talent timeline in countries such as Uzbekistan, where the AI Readiness Index ranking has improved from 158 to 79 over four years but where applied banking-AI expertise remains scarce. Fourth, banks should plan for the responsible adoption of generative AI as an operational layer. Local-language proprietary models, of the kind developed by TBC Uzbekistan, materially improve customer-facing performance and reduce the externalization of sensitive data to foreign foundation-model providers, partially mitigating data-sovereignty concerns.

The implementation of AI technologies in commercial banks generates significant economic efficiency gains—through cost reduction, revenue uplift, risk-decision improvement, and infrastructure modernization—and simultaneously introduces a new class of security risks linked to the technology itself, to its operational deployment, and to its adversarial use. These two dimensions are mutually constitutive: poor governance erodes efficiency, and inefficient governance produces security failures. Treating efficiency and security as competing objectives misrepresents the underlying economics. The DAOS framework—Data integrity, Algorithmic accountability, Operational resilience, Supervisory convergence—offers a structured way to align the two dimensions. Empirical evidence from advanced banking systems (the United States, the European Union, China) and from a transition economy (Uzbekistan) supports the claim that the institutions realizing the largest efficiency gains are those that have invested most rigorously in the underlying security and

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governance infrastructure. For commercial banks in transition economies, the analysis suggests three priorities: pairing AI investment with proportional governance budgets, supporting the development of national AI-banking standards, and investing in domestic talent and language-specific models that retain data sovereignty. For supervisors, the priority is to develop AI-specific guidance that converges with international practice while reflecting local institutional realities. For the research community, the analysis identifies three open questions: the optimal sequencing of efficiency and security investments; the quantification of avoided losses from preventive controls; and the comparative effectiveness of different governance architectures in different national settings. The trajectory of AI in commercial banking is not, in the end, a story about technology. It is a story about institutional capacity—about whether banks can govern systems that are faster, more autonomous, and more deeply embedded than any previously deployed in the financial sector. The institutions that succeed in this task will combine economic ambition with security discipline; the institutions that fail will treat one as a constraint on the other. The framework and recommendations advanced in this article are intended to support the former.

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