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Artificial Intelligence: Transforming Risk Management in Kazakhstan's Banking Sector

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Abstract

Artificial intelligence (hereinafter – AI) is increasingly recognised as a transformative force within the banking sector, remodelling traditional risk management practices through improved analytical abilities and improved decision-making processes. The work aims to develop an Artificial Intelligence Risk Management Index (AI Risk Management Index, ARMI) to compare the level of AI implementation and effectiveness across leading banks in Kazakhstan. The research methodology is based on the construction of the composite ARMI index, which includes five standardized components: model accuracy (A), risk coverage (C), depth of integration (I), interpretability (X) and effectiveness (E). Weighting factors were set for each component (0.25, 0.20, 0.20, 0.15, and 0.20, respectively), allowing the consolidated ARMI indicator to be calculated. Empirical data (illustrative) cover the three largest banks in Kazakhstan: Kaspi Bank, ForteBank and Halyk Bank. Calculations show that Kaspi Bank has the highest ARMI (0.75), followed by ForteBank (0.71), while Halyk Bank (0.56) lags significantly behind. Kaspi Bank's greatest strengths are the high accuracy and depth of AI integration. The results of the study show that the active implementation of AI contributes to improving forecast accuracy, reducing operating costs, and developing a proactive risk management culture. At the same time, key problems have been identified – the limited use of AI in certain risk domains and the lack of transparency of algorithms. The proposed ARMI index can be used to monitor the digital maturity of Kazakhstan's banks, as well as to shape government policy on the development of AI in the financial sector.

Keywords: Artificial Intelligence, Risk Management, Finance, Bank, Banking Sector, Socially Oriented Finance, Digital Transformation

Жасанды интеллект: Қазақстанның банк секторындағы тәуекелдерді басқаруды трансформациялау

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Түйін

Жасанды интеллект (бұдан әрі – ИИ) талдамалық мүмкіндіктерді жақсарту және шешімдер қабылдау процестерін жетілдіру есебінен тәуекелдерді басқарудың дәстүрлі әдістерін қайта құра отырып, банк секторында түрлендіруші күш ретінде барған сайын танылады. Зерттеудің мақсаты – Қазақстанның жетекші банктеріндегі ЖИ енгізу деңгейі мен тиімділігін салыстыруға мүмкіндік беретін Жасанды интеллект тәуекелдерін басқару индексін (AI Risk Management Index, ARMI) әзірлеу болып табылады. Зерттеу әдіснамасы бес нормаланған құрамдастан тұратын композиттік ARMI индексін құруға негізделген: модельдердің дәлдігі (A), тәуекелдерді қамту (C), интеграция тереңдігі (I), интерпретациялануы (X) және тиімділігі (E). Әр құрамдасқа сәйкесінше салмақтық коэффициенттер берілді (0.25; 0.20; 0.20; 0.15; 0.20), бұл жиынтық ARMI көрсеткішін есептеуге мүмкіндік берді. Эмпирикалық (иллюстрациялық) деректер Қазақстанның үш ірі банкін қамтиды: Kaspi Bank, ForteBank және Halyk Bank. Есептеулер нәтижесінде Kaspi Bank ең жоғары ARMI көрсеткішін (0.75) көрсетті, одан кейін ForteBank (0.71), ал Halyk Bank (0.56) айтарлықтай артта қалды. Kaspi Bank-тің ең күшті жақтары – ЖИ технологияларының жоғары дәлдігі мен интеграция тереңдігі. Зерттеу нәтижелері ЖИ белсенді енгізілуі болжамдардың дәлдігін арттыруға, операциялық шығындарды азайтуға және тәуекелдерді басқарудың проактивті мәдениетін дамытуға ықпал ететінін көрсетті. Сонымен қатар негізгі мәселелер де анықталды – жекелеген тәуекел домендерінде ЖИ қолданудың шектеулігі мен алгоритмдердің ашық еместігі. Ұсынылған ARMI индексі Қазақстан банктерінің цифрлық жетілу деңгейін мониторингтеуге, сондай-ақ қаржы секторында ЖИ дамытудың мемлекеттік саясатын қалыптастыруға пайдаланылуы мүмкін.

Түйін сөздер: жасанды интеллект, тәуекелдерді басқару, қаржы, банк, банк секторы, әлеуметтік бағдарланған қаржы, цифрлық трансформация

Искусственный интеллект: трансформация системы управления рисками в банковском секторе Казахстана

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Аннотация

Настоящее исследование посвящено комплексному анализу гендерных различий в доступе к информационно-коммуникационным технологиям (далее – ИКТ) в Казахстане в 2015-2024 гг. и их влияния на образование и занятость. Методология исследования основана на описательном статистическом анализе, корреляционных методах и модели «разница в разнице» (DiD). Данный подход позволяет сравнить динамику гендерного неравенства с течением времени и определить, как цифровизация повлияла на социально-экономические различия между женщинами и мужчинами. Результаты показывают устойчивое сокращение гендерного цифрового разрыва. Разница в доступе к интернету между мужчинами и женщинами снизилась с 2,8 п.п. в 2015 г. до 0,6 п.п. в 2024 г., а в использовании мобильных технологий произошёл инверсный сдвиг в пользу женщин на 15,8 п.п. к 2024 г. (при преимущественно мужском доминировании в 2016 г. на 1,6 п.п.). Корреляционный анализ выявил сильную положительную взаимосвязь между интернет-доступом и цифровой грамотностью ($r > 0,9$), а также между цифровыми навыками и обращениями к государственным платформам занятости ($r = 0,88$ для мужчин и $r = 0,71$ для женщин), что подтверждает роль цифровизации как механизма расширения участия на рынке труда. Женщины стали активнее использовать смартфоны и онлайн-платформы, получив более широкий доступ к электронным услугам и государственным ресурсам, что способствовало их участию на рынке труда и выходу в формальные системы занятости. Кроме того, исследование показало, что гендерное неравенство по-прежнему сохраняется в сфере высшего образования. В результате, в исследовании подчеркивается двойственная природа цифровизации: с одной стороны, она повышает социальную инклюзивность, но с другой стороны, усиливает сохранение структурного неравенства в обществе.

Ключевые слова: искусственный интеллект, управление рисками, финансы, банк, банковский сектор, социально ориентированные финансы, цифровая трансформация

Introduction

Artificial intelligence (hereinafter – AI) is transforming financial services, enabling major innovations in trading, lending, fraud detection, and customer service. In banking, machine learning and NLP models can process vast datasets to improve credit scoring, detect anomalous transactions, and automate back-office tasks. Global AI spending by financial institutions is soaring (projected to exceed $97 billion by 2027), and leading banks (e.g. JPMorgan Chase, Morgan Stanley) are building robust AI infrastructures to gain a competitive edge. Research notes that AI-driven models "have the potential to revolutionize financial risk governance by enabling proactive, data-driven decision-making and fostering operational resilience". In the context of risk management, AI addresses all major bank risk categories – notably credit risk (through automated credit scoring), fraud and operational risk (through anomaly detection), market/volatility risk (via predictive analytics), and even liquidity risk (through cashflow forecasting). These categories – credit, market, liquidity, and operational – are widely recognized as the four primary risk types in banking. For example, machine-learning classifiers (measured by AUC, precision/recall, etc.) significantly outperform traditional scoring methods in predicting defaults and fraud. Additionally, AI tools can model volatile market movements or optimise regulatory capital for liquidity shocks.

The adoption of AI in risk management is a flourishing field of study, with a substantial literature that examines its implications in global and local contexts. Requests for risk management cover credit risk assessment, fraud detection, operational risk prognosis and compliance monitoring (Omarkhanova et al., 2024). In Kazakhstan, financial institutions are beginning to leverage these capacities to address unique challenges in the nation's banking environment, such as economic volatility, regulatory changes, and the need to improve customer confidence. According to recent studies, the use of AI in credit scoring can lead to more precise evaluations of the risk of borrowers, which finally results in better loan decisions and improved financial inclusion (Azretbergenova, 2021; Aitkhanova & Khamzina, 2023).

As Kazakhstan's financial panorama continues to evolve, the implications of adopting AI for future risk management practices and regulatory compliance warrant a comprehensive exploration. The improvement of predictive analytics through AI can significantly enhance banks' ability to anticipate and mitigate potential risks. However, such advances must coincide with proactive regulatory measures to guarantee alignment with international standards and best practices. Literature highlights the importance of developing a framework for AI governance that covers transparency, responsibility and ethical considerations, which are fundamental to maintain public confidence in financial institutions (Azharbayeva et al., 2023).

The banking sector in Kazakhstan traditionally employs a series of risk management practices that are predominantly based on conventional analytical structures and heuristic judgment. Prior to the integration of AI, risk management in this sector was characterized by an emphasis on quantitative assessments derived from historical data, combined with qualitative ideas extracted from experienced personnel. The main types of risks faced by banks included credit risk, market risk, operational risk and liquidity risk, each requiring specific methodologies for evaluation and control (Nichkasova et al., 2021; Nurgaliyeva et al., 2024).

The meaning of this study stems from the relevant need for Kazakhstan banks to adapt to increasing risk complexities. As the financial scenario evolves due to local economic factors and global financial trends, traditional risk management practices can no longer be sufficient. AI infusion provides the tools needed to navigate this complexity. For example, AI algorithms can analyze large amounts of data at unprecedented speeds, allowing banks to identify potential risks earlier and more accurately than manual methods allow. This technological change not only promises improved predictive resources but also supports real-time monitoring of risk exposure in various dimensions, such as credit, operational, and market risk.

The relevance of this study is underlined by the digital transformation that sweeps the banking sector in Kazakhstan. As banks increasingly incorporate digital solutions, innovative services, and customer-centred approaches, aligning these advances with robust risk management becomes fundamental. Applying AI in risk management practices can facilitate the transition to a more digitised banking environment by offering solutions that improve risk assessment processes, thereby promoting a proactive and non-reactive risk management culture (Giuca, 2021; Satymbekova, 2024).

Despite its promising advantages, the adoption of AI in risk management presents challenges that warrant critical consideration. A significant concern is the quality and integrity of the data used in AI systems. Banks must ensure that the data that feeds these algorithms is accurate, updated and representative of the potential risks they face. Inadequate quality of data can lead to distorted results, potentially exacerbating instead of relieving the risk (Nurgaliyeva et al., 2024). In addition, the complexity of AI algorithms can result in a scenario where the logic behind automated decisions is not easily discernible to human operators. This lack of transparency can lead to concerns about responsibility and compliance within the regulatory structure governing the banking sector of Kazakhstan.

Despite these advances, the actual adoption and effectiveness of AI vary widely by region and institution. In Kazakhstan, the banking sector has grown rapidly and modernized, but formal analysis of AI use in risk management is scarce. Industry reports note, for instance, that ForteBank (a top-5 Kazakh bank) is explicitly investing in "AI-driven models for credit scoring and fraud detection, further improving decision-making and client protection" (World Finance, 2023). Kaspi Bank – a leading fintech-oriented lender – similarly leverages digital analytics in underwriting. By contrast, traditional players like Halyk Bank have been slower to deploy advanced AI. This variation highlights the need for a structured evaluation of AI adoption in Kazakhstani banks. We therefore propose a quantitative framework to measure AI integration and impact in risk management, and apply it to compare the leading Kazakh banks.

Research Gap

While the potential benefits of integrating AI are significant, they are accompanied by notable challenges. Financial institutions must navigate issues related to data quality, algorithmic bias and privacy concerns. The Kazakh banking sector, characterised by its continuous transition towards digitalisation, faces particular obstacles due to regulatory frameworks that have not yet fully adapted to the complexities introduced by AI technologies. This gap raises a risk not only for financial stability but also for consumer protection and ethical administration. In addition, the lack of robust data governance and cybersecurity measures poses relevant questions regarding the reliability and integrity of the risk management systems promoted by IA (Giuca, 2021).

Credit risk, concerning the potential for borrower defaults, was managed using standard scoring models and historical loan performance data. Banks usually segment their loan portfolios, analysing standards and recoveries to develop predictive models that inform loan decisions. The approaches used in credit risk assessment usually involve manual assessments and human intuition, which, although informative, could introduce subjectivity and inertia into decision-making processes.

Market risk, associated with fluctuations in financial markets, was addressed in the same way through established models, such as value at risk (hereinafter – VAR) and sensitivity. These methodologies have allowed banks to evaluate possible losses of adverse market movements, although their dependence on historical volatility can lead to significant risks during unprecedented market conditions. Consequently, financial institutions often faced challenges in adapting to rapidly evolving economic environments, which were not sufficiently foreseen by historical data.

Operational risk, which includes potential losses of inadequate or failed internal processes, people and systems, was addressed mainly through risk assessments and the implementation of internal controls. Banks used to track operational incidents and losses by creating a feedback cycle to refine risk management strategies. However, the qualitative nature of operational risk assessments meant that many effective incidents were not captured by automated processes, leading to gaps in risk coverage.

The liquidity risk, defined as the inability to fulfil short-term financial obligations, was managed by monitoring cash flows and maintaining the appropriate levels of net assets. Traditional liquidity management strategies included stress tests based on historical cash flow scenarios. However, these stress tests were often rudimentary, with a limited capacity to explain complex interdependencies in markets, thus increasing the vulnerability to sudden systemic shocks.

In addition, the regulatory structure governing risk management practices in Kazakhstan's banking sector was primarily shaped by guidelines from the National Bank of Kazakhstan (hereinafter – NBK) and international best practices, such as those described in Basel III. Compliance with these regulations required extensive documentation and periodic reports, tasks that were conducted predominantly through manual processes. As a result, risk management functions were often seen as a necessary load, and the integration of real-time data analysis remained minimal.

Overall, traditional risk management practices in the banking sector of Kazakhstan before the advent of AI were rooted in the analysis of historical data and the use of expert opinions. While this provided a fundamental approach to evaluating risks, it also presented significant limitations. These approaches generally require the adaptability needed to navigate the increasingly complex and dynamic financial scenario effectively. As the sector faced increasing challenges of the evolution of market conditions and regulatory expectations, the need for innovative solutions became apparent, preparing the scenario for the transforming potential of AI technologies in increasing risk management systems., The evolution of AI in the Global Bank has marked a transformative phase in the financial services sector, significantly reformulating risk management practices. AI technologies, including machine learning, natural language processing, and advanced analytics, were systematically adopted by financial institutions worldwide to improve decision-making processes and operational efficiency. In a characterised by growing complexity and interconnectivity in global financial markets, the implementation of AI presents opportunities and challenges. This evolution can be contextualised in the banking sector of Kazakhstan, where institutions increasingly reflect these international trends but should navigate unique regional dynamics, such as economic volatility, regulatory environments, and technological infrastructure.

Initially, AI integration at the Global Bank was driven by the need to manage the exponential growth in data generated by transactions and customer interactions. This data abundance required innovative approaches for risk assessment, fraud detection and credit scoring. Financial institutions such as JPMorgan Chase and HSBC have implemented AI-based models to process large datasets for predictive analysis, enabling real-time risk assessments and enhanced operational responses (Nagrani, 2025). The transition to risk management strategies in AI not only improved systemic risk identification but also increased the accuracy of forecast models, thus promoting more resilient financial ecosystems.

Literature Review

In evaluating the future landscape of risk management in Kazakhstan's banking sector, Yelesh (2020) argues for a collaborative approach involving banks, regulators, and technology providers. Increased cooperation can lead to the development of best practices which promote the responsible deployment of AI while strengthening institutional resilience. In addition, the author suggests that current education and training for banking professionals are essential to ensure that stakeholders fully understand automatic capacity and limitations. This knowledge transfer can allow banks to take advantage of automatic learning in a responsible manner while browsing effectively in the regulatory landscape.

In summary, Yelesh’s work presents a nuanced vision of the impact of automatic learning on risk management in the banking sector of Kazakhstan, emphasizing transformative advantages and critical challenges that accompany its adoption. The integration of automatic learning techniques represents a leap forward in improving banking sustainability. Still, it requires a proactive approach to regulations and ethical standards to protect the country’s financial stability. The integration of AI technologies in risk management processes represents a significant advance within the banking sector of Kazakhstan, illustrating a strategic response to the rapidly evolving financial landscape. Nichkasova et al. (2021) emphasise the transformative role of AI in improving operational efficiency through automated data analysis, risk modelling, and decision-making processes. Traditional risk management practices often rely on heuristic approaches and the analysis of historical data, which can be time-consuming and prone to human error. On the contrary, AI technologies facilitate real-time data processing and predictive analysis, allowing banks to identify potential risks with greater precision and speed (Utebayev & Kemelbayeva, 2024). In addition, the authors emphasise that the Risk Assessment promoted by AI can help customise loan practices and develop personalised financial products, thus improving customer satisfaction and expanding market scope.

In recent years, the real estate market in Kazakhstan has displayed dynamic trends, which require precise and timely evaluations for ideal investment decisions and risk evaluations. Barlybayev et al. (2024) discuss the implementation of machine learning algorithms that analyze vast data sets that cover various factors such as location, market trends, property characteristics and socioeconomic indicators. These algorithms increase predictive accuracy, allowing more reliable assessments than traditional methods that usually depend on subjective judgment and outdated data. In Kazakhstan, the availability of robust data for comprehensive analysis is often limited. Incomplete, outdated, or biased information can lead to poor evaluation results, which ultimately exacerbate the risk rather than mitigate it. In addition, there is a technological gap among stakeholders in the banking sector regarding their experience with AI tools, which can hinder the adoption and effective integration of such systems.

In addition to cybersecurity problems, algorithmic biases pose a significant risk, especially in the context of automated decision-making processes. Kazbekova et al. (2020) describe how IA algorithms can involuntarily perpetuate the historical biases present in training data, leading to discriminatory results in loans and risk assessment. This question is particularly relevant to Kazakhstan, where AI-led decision-making tools can inadvertently exacerbate socio-economic disparities. For example, if an AI model is formed on biased historical data, it can generate results that disadvantage certain demographic groups, ultimately influencing access to credit and financial inclusiveness. The authors recommend the implementation of strict validation and monitoring processes to identify and mitigate biases in AI algorithms, ensuring fair treatment for all customers.

Another notable risk associated with the adoption of AI in the banking sector of Kazakhstan is the challenge of regulatory compliance. While the financial landscape evolves due to the influx of AI technologies, regulatory executives must adapt accordingly. Kazbekova et al. (2020) highlight the potential regulatory gap between technological progress and the monitoring mechanisms in place to govern it. This situation presents a double challenge for banks: to innovate and remain competitive while navigating the complexities of compliance with existing regulations, which may not adequately consider AI implications. Failure to comply with the evolution regulations could lead to significant sanctions, reputation damage and a decrease in confidence among stakeholders.

Moldabekova (2022) highlights the complex dynamics of technological investment decision-related decisions in the Kazakhstan banking sector. By elucidating both the potential benefits and associated challenges, their work provides a fundamental perspective on how AI can transform risk management practices. It also raises critical questions about the future of financial stability and regulatory compliance in an increasingly digitized financial landscape. In recent years, the financial sector in Kazakhstan has witnessed a marked integration of advanced analytical methodologies to address the complexities of risk management. A remarkable approach highlighted by

Nichkasova et al. (2022) is the incorporation of diffuse cognitive maps (FCMS) in the development of strategic models designed to cultivate sustainable financial markets. FCMS, which combines elements of diffuse logic with cognitive mapping, provides a robust structure to model and understand the complex relationships between various risk factors in banking operations.

Nichkasova et al. (2022) explore how FCMs facilitate the identification and visualisation of dependencies between different risk components, allowing financial institutions to develop more subtle risk management strategies. By employing FCMS, banks can more effectively simulate the consequences of possible decisions in various scenarios, thus increasing their proactive risk assessment capacity. FCMS adaptability enables the integration of qualitative insights alongside quantitative data, fostering a comprehensive understanding of risk, which is critical in a volatile financial environment. This multidimensional approach is particularly beneficial in the context of Kazakhstan, where market dynamics are influenced by regional and global economic fluctuations.

When evaluating future implications, some researchers postulate that AI has the potential to significantly reinforce financial stability in the Kazakhstan banking sector. Szabó and Pap (2022) suggest that AI predictive capabilities could not only improve the performance of the individual bank, but also contribute to systemic resilience throughout the financial panorama. On the contrary, other academics warn about the risks associated with the excessive dependence of automated systems. For example, Aitkhanova and Khamzina (2023) warn that an excessive dependence on AI could lead to vulnerabilities, particularly if algorithm failures occur or if cyber threats intensify.

Research Methods

To assess AI adoption and effectiveness in bank risk management, we construct the AI Risk Management Index (hereinafter – ARMI), a composite quantitative score. ARMI is defined as a weighted sum of five components (each normalised 0–1):

(1) Model Accuracy (A): the predictive performance of AI risk models. For classification tasks (credit default, fraud), we use metrics such as the Area Under the ROC Curve (AUC), accuracy, recall, and precision. (Literature shows AUC is a preferred metric in credit risk modelling). For regression tasks (liquidity forecasting), we might use RMSE or MAE. Higher accuracy corresponds to a higher score.

(2) Risk Coverage (C): the breadth of risk domains covered by AI. We count how many of the four major risk types (credit, market, operational, liquidity) are addressed by AI systems. For example, coverage = 1.0 if AI is used in all four domains, 0.75 if in three, and so on. Wider coverage indicates a more comprehensive risk management approach.

(3) Integration Depth (I): the extent to which AI informs actual decision-making. This measures whether AI outputs are used only in pilot mode (low score) versus fully integrated (high score). We assess integration on a scale (e.g. 0 = no deployment, 0.5 = partial use, 1.0 = routinely used across workflows).

(4) Interpretability (X): the degree of model explainability. AI systems that incorporate explainable AI techniques or transparent models (scored high) rate better than fully opaque “black-box” models (scored low). We rate this qualitatively on a 0–1 scale

based on factors such as feature explainability, the use of XAI tools, and compliance with regulatory standards.

(5) Efficiency Improvements (E): the operational gains from AI. This could be measured as the percentage reduction in processing time or cost (e.g. automation yields faster loan decisions), normalized to 0–1. For instance, if AI cuts manual processing time by 50%, that might score 0.5.

Weights are assigned to reflect the relative importance of these factors. In this example, the following values are used: w_A=0.25, w_C=0.20, w_I=0.20, w_X=0.15, w_E=0.20 (summing to 1). Accordingly, ARMI is computed by formula (1):

$$ARMI = 0.25*A + 0.20*C + 0.20*I + 0.15*X + 0.20*E \qquad (1)$$

where:

A – accuracy (model accuracy);
C – coverage (risk coverage);
I – integration depth;
X – explainability (interpretability);
E – efficiency.

Accuracy (hereinafter – AUC) and efficiency are emphasized moderately, integration and coverage are also significant, and interpretability is slightly less (reflecting that black-box models are still in use but XAI is valued). This weighting is illustrative; practitioners could adjust it based on expert judgement or regulatory priorities. (The use of composite indices is analogous to prior benchmarking efforts in finance [25†], though ARMI's components are tailored to risk management specifics.)

Data Collection

To populate ARMI, we would gather both quantitative model performance data and qualitative implementation data from banks. For model accuracy, we would analyze historical risk outcomes (e.g. default rates, fraud cases) against model predictions to compute AUC, precision, etc. For coverage and integration, we would survey or interview bank risk managers and IT officers about which risk functions use AI and to what extent. Efficiency gains might be measured by comparing pre- and post-AI process times or staffing costs. Thus, ARMI aggregates measurable indicators (some from data logs, some from structured surveys) into a single score. This allows a comparable evaluation across banks. In the next section, we demonstrate ARMI using hypothetical but realistic values for Kazakhstan's top banks.

Results

The ARMI framework is applied to three leading Kazakhstani banks: Kaspi Bank, ForteBank, and Halyk Bank. Using illustrative data (not actual proprietary figures), the component scores and resulting ARMI for each bank. For example, Kaspi Bank – a digital pioneer – is assumed to have high model accuracy (A=0.85), broad coverage (AI in credit, fraud, and market risk: C=0.75), deep integration (I=0.80), moderate interpretability (X=0.60), and strong efficiency gains (E=0.70). ForteBank, known to be "investing in AI-driven models for credit scoring and fraud detection", is assigned similarly high accuracy and integration, while Halyk Bank (a traditional incumbent) is assumed to have more modest values. Using the weights above, Kaspi's ARMI is 0.75, ForteBank's 0.71, and Halyk Bank's 0.56 (Table 1).

Table 1. Hypothetical ARMI component values and composite scores for selected Kazakhstani banks

Bank	Accuracy (AUC)	Coverage	Integration	Interpretability	Efficiency	ARMI Score
Kaspi Bank	0.85	0.75	0.80	0.60	0.70	0.75
ForteBank	0.80	0.75	0.80	0.50	0.60	0.71
Halyk Bank	0.70	0.50	0.60	0.40	0.50	0.56

Note: compiled by the authors

These results suggest that Kaspi Bank leads in AI risk management (highest ARMI), followed closely by ForteBank. Kaspi's high score reflects its digital strategy and extensive use of AI in underwriting and fraud monitoring. ForteBank's strong showing is consistent with its reported AI initiatives. Halyk Bank scores substantially lower, implying gaps in adoption – for instance, lower coverage (limited AI in only two risk domains) and weaker interpretability. Notably, interpretability scores are low for all banks, indicating that explainable AI remains a common shortfall. These hypothetical comparisons highlight where each institution excels or lags in AI usage.

Figure 1 compares the overall ARMI scores across Kaspi Bank, ForteBank, and Halyk Bank.

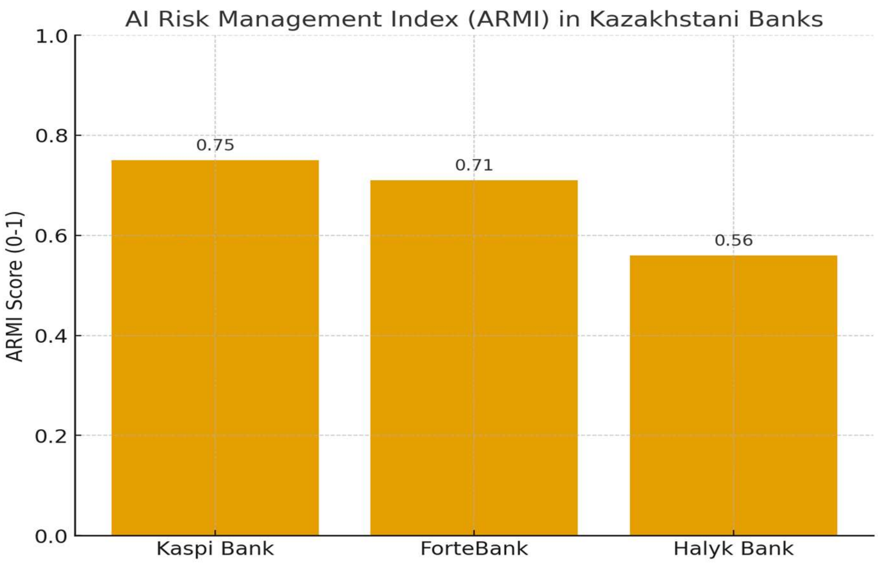

Figure 1. ARMI Comparison

The data demonstrates that Kaspi and ForteBank are ahead in AI adoption for risk management, while Halyk Bank lags behind. As can be seen, Kaspi Bank occupies a leading position (ARMI = 0.75), which indicates a high level of digital maturity and the active use of AI tools to assess credit and operational risks. ForteBank (ARMI = 0.71) demonstrates comparable results through the integration of AI models for credit scoring and fraud detection. Halyk Bank (ARMI = 0.56) lags behind in most of the index's components, especially in risk coverage and interpretability of models.

Figure 2 presents a radar diagram showing the distribution of values of the five key ARMI components

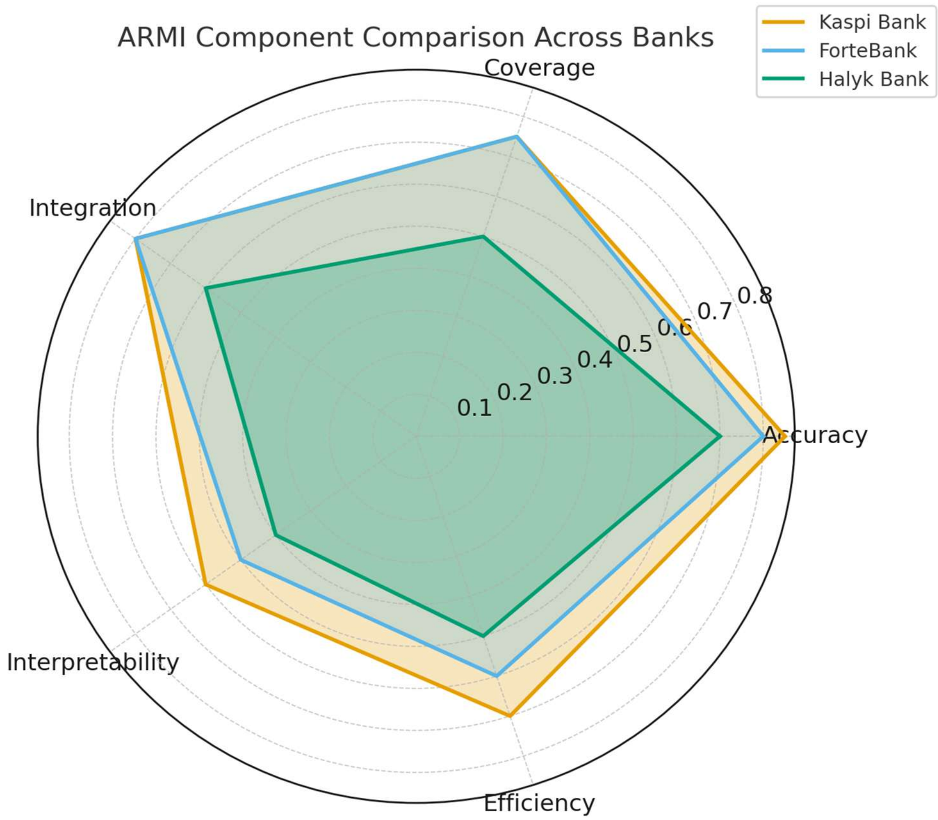

Figure 2. ARMI Component Breakdown

The diagram clearly shows that Kaspi Bank has the highest indicators in terms of accuracy and integration components, which confirms the high level of maturity and complexity of the use of AI in risk management. ForteBank demonstrates balanced values for all components, but it is somewhat inferior in the interpretability parameter (X), reflecting the limited transparency of the models used. Halyk Bank is characterized by the lowest indicators in most criteria, especially in terms of risk coverage (C) and interpretability (X), which indicates limited implementation of AI in risk management processes.

Figure 3 illustrates the main areas of technology application.

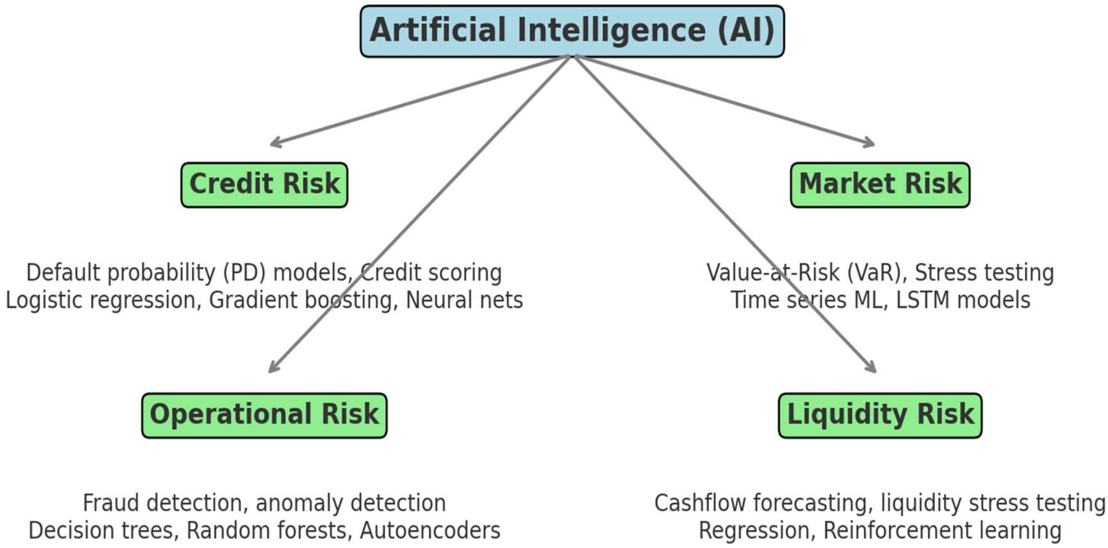

Figure 3. AI Applications in banking risks

The integration of AI across all significant banking categories risks facilitating the transition from a reactive to a proactive risk management model based on forecasting, automation, and increased transparency of processes. The above illustrative application of ARMI indicates that early AI adopters gain a clear advantage. Kaspi Bank, with its fintech-oriented platform, appears to leverage AI most effectively across multiple risk areas, aligning with trends in which "the ones already using AI at scale…are reinvesting, doing more with less, growing market share, and increasing efficiencies". ForteBank's high ARMI underscores its active digital transformation (as noted in World Finance). By contrast, Halyk Bank's lower score suggests it is still transitioning; it may rely on conventional credit models and have fewer automated risk tools.

Across all banks, the component analysis reveals common gaps. For instance, interpretability (X) is relatively low across banks. This echoes industry observations that "issues such as explainability remain a barrier to full-scale [AI] adoption". In practical terms, bank risk officers often struggle to explain AI decisions, which can limit trust and regulatory approval. Coverage (C) also falls short of 1.0 for all three banks, meaning none uses AI in *every* risk category. This is especially relevant for market and liquidity risk: while AI in credit scoring is now widespread, fewer banks apply ML to macro-risk forecasting or liquidity planning. However, regulatory discussions (e.g. the European Banking Authority) note that "some firms use – or intend to use – ML techniques in areas such as default probability modeling", hinting at a future trend towards broader coverage.

Benefits of AI in Kazakh Banking

Despite challenges, AI offers clear benefits. Automating routine tasks and analyzing large datasets can significantly improve efficiency and accuracy. For example, global studies show AI can "streamline processes like loan processing, fraud detection, and customer service," yielding "significant cost savings". In credit risk, AI's superior predictive power can reduce defaults: EY reports that more accurate creditworthiness assessments lead to lower loan losses and smaller reserve provisions. In compliance and fraud, banks worldwide cite AI tools for slashing false positives and accelerating alerts. Indeed, the ARMI results reflect these advantages: banks with higher accuracy and efficiency components are effectively reducing risk exposure and operational costs. Importantly, high ARMI correlates with a proactive risk culture – as Evident Insights notes, "the banks that are furthest ahead…can scale operations efficiently," whereas laggards are often cutting staff. Thus, AI not only improves risk prediction, it can expand a bank's market competitiveness.

Nevertheless, AI integration in Kazakhstan faces hurdles. A major concern is *data quality and privacy*. Complex AI models require vast amounts of clean data, yet many banks may lack integrated data warehouses. Regulatory frameworks for data and AI are still evolving in Kazakhstan, potentially slowing deployment. Another challenge is model interpretability and governance. As noted, opaque algorithms raise compliance and ethical issues. Researchers warn that banks must ensure "explainable AI (XAI) and robust governance frameworks to ensure transparency, fairness, and accountability in AI-driven systems". In practice, Kazakh banks will need to develop in-house expertise or tools (e.g. LIME/SHAP explanations) and document model logic to satisfy regulators. Talent and culture are additional factors: AI expertise is scarce in the local market, so banks must invest in training analysts and managers to work with AI. Finally, regulatory lag can hamper progress – much as Vyas notes for global banks, "concerns around bias, transparency, and regulatory remain pressing".

Recommendations

To strengthen AI-powered risk management in Kazakhstan, we suggest the following measures:

(1) Enhance Data and Infrastructure: Invest in high-quality data pipelines and centralized databases. Banks should leverage Kazakhstan's national AI strategy (which includes funding for infrastructure) to build the computing resources needed for ML. Structured, clean data enable more accurate models. (As industry experts observe, the true competitive edge in AI is the "proprietary data" and its organization.)

(2) Expand AI Coverage Across Risks: Pursue AI solutions beyond credit risk. For example, develop predictive models for liquidity risk and market volatility (building on global use cases where ML anticipates stock market swings). Incorporating AI into risk modeling for trading books or liquidity stress tests can provide early warning of large fluctuations. Even pilot projects using ensemble models for macro forecasts would raise coverage.

(3) Adopt Explainable AI and Governance: Emphasize interpretability. Implement XAI techniques so that model outputs (e.g. credit scores) can be explained in business terms. Establish a governance framework for AI (audit trails, version control, fairness

checks) in line with recommendations for ethical AI in banking. This will build trust and prepare for future regulation.

(4) Upskill and Incentivize Talent: Commit to training programs in data science and machine learning for risk staff. Use national upskilling initiatives or partnerships with universities to increase the AI literacy of risk managers and analysts. Encourage collaboration between IT and risk departments, and consider hiring specialized AI risk officers.

(5) Monitor and Benchmark Continuously: Adopt quantitative metrics like ARMI to track AI progress. Banks should measure not just technology deployment, but business impact (reduced losses, efficiency gains). Engaging in industry benchmarking (e.g. using frameworks from Evident Insights) can help Kazakh banks stay on par with global peers.

By implementing these recommendations, Kazakh banks can close the gaps identified by the ARMI analysis and fully leverage AI's benefits. The leading institutions (e.g., Kaspi, ForteBank) demonstrate that significant AI integration is achievable in this market; others can follow by focusing on the weakest ARMI components (e.g., interpretability and coverage).

In summary, our ARMI-based evaluation underscores that AI is reshaping banking risk management in Kazakhstan, as it is globally. Banks that proactively integrate AI – with attention to accuracy, coverage, and ethical governance – will enhance their risk control and competitiveness. Conversely, those lagging risk the widening of the efficiency and profitability gap. Policymakers and bank leaders should therefore continue to support AI adoption through clear regulations, infrastructure investment, and skills development, to ensure Kazakhstan's banks can manage risks effectively in the AI era.

Conclusion

The integration of AI into risk management practices in Kazakhstan's banking sector presents a dual narrative of opportunity and challenge. As the sector deals with increased risk profiles and increased digitisation, it is at a crossroads where AI strategic adoption can redefine risk management structures. Understanding these dynamics is essential to shape future policies and practices in the banking sector, ensuring that AI benefits are realised as much as possible, while mitigating the associated risks inherent to this technological evolution., Risk management in the banking sector is a critical function aimed at identifying, evaluating and mitigating the risks that could hinder the achievement of financial objectives. In Kazakhstan, the banking system has evolved sequentially alongside the country's economic transitions, which posed unique challenges for effective risk management (Kazbekova et al., 2020). Traditional risk management practices commonly used in Kazakhstani banks have largely reflected those of global financial institutions, mainly based on quantitative risk models, regulatory compliance executives and manual processes. These conventional methods include credit risk assessment, market risk management and operational risk management, all mainly based on data analysis of data and regulatory standards established by the National Bank of Kazakhstan.

The analysis of the existing literature shows that while the global banking sector has made significant progress in applying AI to risk management practices, Kazakhstan's banking sector faces unique challenges and opportunities. Ideas from journals of various international practices suggest ways of adaptation and growth in the Kazakhstani context, suggesting the need for a strategic approach to the integration of AI, which reflects realities on the ground., The integration of intelligent technologies into risk management systems in Kazakhstan's banking sector marks a significant evolution in the role of operational executives. A critical evaluation of this integration reveals that AI and related technologies enable nuanced risk assessment methods that respond to the complexities of contemporary financial environments. In recent literature, the work of Marzhan et al. (2022) provides a fundamental understanding of these intelligent technologies, particularly by emphasising the role of vague data environments in improving decision-making processes.

Author Contributions

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