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ARTIFICIAL INTELLIGENCE-BASED RISK MANAGEMENT FOR THE BANKING SECTOR: IMPACT AND CHALLENGES

The aim of this study is to comprehensively examine the impact of artificial intelligence (AI) technologies on risk management in the banking sector. The research focuses on how machine learning, natural language processing, and predictive analytics enhance credit scoring, fraud detection, and regulatory compliance. A mixed-method approach was applied, including a systematic literature review, machine learning based analysis of open banking datasets (Kaggle), and a survey of 200 bank employees in the Middle East. The findings demonstrate that ensemble models such as XGBoost and Random Forest significantly outperform traditional techniques in prediction accuracy and classification efficiency. The scientific novelty lies in the development of a comprehensive framework for integrating AI into banking risk management systems while addressing ethical and regulatory concerns, practices, and minimize financial losses.

Furthermore, the study identifies key challenges, including data privacy concerns, model interpretability, and regulatory constraints, that may hinder the effective integration of AI in banking. The research concludes that AI-driven models have the potential to revolutionize financial risk governance by enabling proactive, data-driven decision-making and fostering operational resilience. Strategic recommendations are provided to guide financial institutions and policymakers in implementing ethical and secure AI frameworks for sustainable innovation.

Keywords: artificial intelligence, risk management, the financial health of banks, machine learning decision-making, banking sector.

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Банк секторында жасанды интеллект негізінде тәуекелдерді басқару: әсері және мәселелері

Бұл зерттеудің мақсаты – жасанды интеллект (AI) технологияларының банк секторындағы тәуекелдерді басқаруға әсерін жан-жақты зерттеу. Зерттеу машиналық оқыту, табиғи тілді өңдеу және болжамды талдау несиелік скорингті, алаяқтықты анықтауды және нормативтік талаптарға сәйкестікті қалай жақсартатынына бағытталған. Жүйелі әдебиеттерді шолуды, ашық банктік деректер жиынын машиналық оқытуға негізделген талдауды (Kaggle) және Таяу Шығыстағы 200 банк қызметкерінің сауалнамасын қамтитын аралас әдіс тәсілі қолданылды. Нәтижелер XGBoost және Random Forest сияқты ансамбльдік модельдер болжау дәлдігі мен жіктеу тиімділігі бойынша дәстүрлі әдістерден айтарлықтай асып түсетінін көрсетеді. Ғылыми жаңалық этикалық және реттеу мәселелерін шешу кезінде АИ-ді банктік тәуекелдерді басқару жүйелеріне біріктіру үшін кешенді негізді әзірлеуде жатыр. Зерттеудің практикалық маңыздылығы оның қаржы жүйесінің тұрақтылығын арттыру, тәуекелдерді бағалау тәжірибесін жақсарту және қаржылық шығындарды азайту үшін қаржы институттары мен реттеушілер үшін қолдану мүмкіндігінде.

Сонымен қатар зерттеу деректердің құпиялылығы мәселелерін, үлгінің интерпретациялануын және реттеуші шектеулерді қоса алғанда, AI-ның банк ісінде тиімді интеграциясына кедергі келтіруі мүмкін негізгі қиындықтарды анықтайды. Зерттеу AI басқаратын модельдер проактивті, деректерге негізделген шешімдер қабылдауға және операциялық тұрақтылықты арттыруға мүмкіндік беру арқылы қаржылық тәуекелдерді басқаруда төңкеріс жасау мүмкіндігіне ие деген қорытындыға келеді. Стратегиялық ұсынымдар қаржылық институттар мен саясаткерлерге тұрақты инновациялар үшін этикалық және қауіпсіз AI негіздерін енгізуге бағытталады.

Түйін сөздер: жасанды интеллект, тәуекелдерді басқару, банктердің қаржылық сақтандырылуы, машиналық оқыту, шешім қабылдау, банк секторы.

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Управление рисками на основе искусственного интеллекта в банковском секторе: влияние и проблемы

Целью данного исследования является всестороннее изучение влияния технологий искусственного интеллекта (ИИ) на управление рисками в банковском секторе. Исследование сосредоточено на том, как машинное обучение, обработка естественного языка и предиктивная аналитика улучшают кредитный скоринг, обнаружение мошенничества и соблюдение нормативных требований. Был применен смешанный подход, включая систематический обзор литературы, основанный на машинном обучении анализ открытых банковских наборов данных (Kaggle) и опрос 200 банковских служащих на Ближнем Востоке. Результаты показывают, что ансамблевые модели, такие как XGBoost и Random Forest, значительно превосходят традиционные методы по точности прогнозирования и эффективности классификации. Научная новизна заключается в разработке комплексной структуры для интеграции ИИ в системы управления банковскими рисками с учетом этических и нормативных проблем. Практическая значимость исследования заключается в его применимости для финансовых учреждений и регулирующих органов для повышения стабильности финансовой системы, улучшения практики оценки рисков и минимизации финансовых потерь.

Кроме того, исследование выявляет ключевые проблемы, включая проблемы конфиденциальности данных, интерпретируемость моделей и нормативные ограничения, которые могут препятствовать эффективной интеграции ИИ в банковское дело. Исследование приходит к выводу, что модели на основе ИИ могут произвести революцию в управлении финансовыми рисками, обеспечивая проактивное принятие решений на основе данных и способствуя операционной устойчивости. Предоставляются стратегические рекомендации для финансовых учреждений и политиков по внедрению этических и безопасных фреймворков ИИ для устойчивых инноваций.

Ключевые слова: искусственный интеллект, управление рисками, принятие решений, машинное обучение, банковский сектор.

Introduction

Effective risk detection, evaluation, and mitigation techniques are vital to ensuring financial stability and protecting client deposits since lending money carries a high default risk and market swings may have an important impact on consumers financial health. As a result, the banking industry heavily depends on strong risk management frameworks. The first phases in risk management in banking are risk identification, assessment, and prioritization. After that, concerted efforts are undertaken to lessen, monitor, and control the possibility or impact of adverse events. Conventional risk management techniques mostly rely on past performance and human judgment, both subject to bias and error. AI provides a more accurate and dynamic approach to risk management because of its capacity to process enormous volumes of data and spot intricate patterns. Banks may improve overall risk mitigation strategies, accelerate decision-making, and more precisely predict future risks by adopting AI-driven models (Gautam, 2023, p.9).

Because banks are subject to an array of risks, involving borrower defaults, noncompliance with short-term obligations, market value fluctuations, internal process errors, and noncompliance with laws and regulations, it is essential to understand the different types of bank risks- credit, market, liquidity, operational, and compliance risk-as well as the significance of having a sound structure (Naeem, 2025). Thus, a well-structured risk management system enables banks to identify potential risks in advance, analyze their severity and probability, implement appropriate controls to mitigate them and continuously monitor their effectiveness. Also, the key points of risk management include the components of the risk management system. These are risk identification, risk assessment, risk mitigation, risk monitoring, risk reporting (Lion, 2024, p.83).

AI's development as a revolutionary tool in a number of sectors, including finance:

Due to its capacity to provide highly automated and data-driven decision-making, AI is rapidly transforming the financial sector.

This leads to increased efficiency, personalized customer experiences, and improved risk management across various financial applications, such as trading, investment advisory, fraud detection, and customer service (Hassan, 2023, p.112).

Essential routes algorithmic trading, risk, assessment, and credit scoring, fraud detection, chatbots and customer support, robo-advisor, market analysis and prediction, compliance, and reports to regulators are some of the ways artificial intelligence is influencing the financial industry. The advantages of AI in finance encompass enhanced efficiency and precision in banking operations, tailored services, improved transaction correctness, expedited decision-making, and the creation of novel business opportunities (Brown, 2024,p.26).

Ai has an enormous effect on the banking sector in addition to it's well known role in risk management. It improves operational efficiency, changes customer service, and directs data-driven decision-making in a number of financial operations sectors.

This streamlines internal procedures and increases the efficiency and personalization of the client experience. AI having a big impact on banking, according to Grand view studies (GVR) and Allied Market Research (AMR).

The value of the banking AI sector grew from \$12.9 billion in 2020 to an incredible \$193,63 billion in 2023, and it is expected to keep on expanding, potentially reaching new heights by 2030. This expansion is driven by a compound annual growth rate (Cagr) of 37,3 % from 2023 to 2030. By empowering banks to compete with Fintech companies in the digital age, artificial intelligence is transforming the banking sector.

According to a 2020 study by National Business Research Institute and Narrative Science, 32 % of banks have implemented AI technologies, including speech recognition and predictive analytics, to gain a competitive edge. AI has the potential to increase revenue significantly across several banking sectors, with corporate and retail banking expected to benefit the most. These industries stand to gain an estimated \$321 billion and \$306 billion in value, respectively, from successful AI implementations (Rolando, 2024a). Machine learning is the most popular AI application in investment banking, with a 60% to 80% utilization rate. Predictive analytics and virtual assistant technologies rank second and third, respectively. Generative artificial intelligence (GenAI) is a powerful force that might provide between \$200 and \$340 billion to the value of the banking industry when taking into account its business environment.

This amount corresponds to 3% to 5% of the industry's overall income, and the banking sector has seen a 9% to 15% boost in profits following the effective implementation of GenAI. In 2023, complaints about point-of-sale problems and unauthorized withdrawals increased by 30%, according to the Consumer Financial Protection Bureau (CFPB). Furthermore, according to a Marketing Standards Board (MSB) poll, 40% of consumers think that unsustainable marketing techniques cause business scandals and marketing inefficiency. Additionally, according to research by the Customer Service Institute (CSI), 50% of consumers have dealt with banking companies, and 60% have met subpar employee attendance policies and bad client relationship management. In growing economies, addressing frequent consumer complaints regarding subpar employee attendance procedures and bad client relationship management becomes essential. AI can improve efficiency and personalization in the customer support process. As a result, marketing results may improve, and consumer happiness and loyalty may rise. Therefore, the descriptive findings of this study may offer valuable recommendations to the financial industry and decision-makers. This would aid in incorporating AI into businesses and formulating action plans to safeguard data privacy and security in the context of AI-driven banking and consumer behavior (Husain, 2022, p.146).

Despite the growing relevance of AI in the banking industry, there are still few well-defined frameworks that show how AI technologies, specifically machine learning, natural language processing, and predictive analytics, may be methodically incorporated into risk management systems. The lack of knowledge about how sophisticated AI models can surpass conventional risk assessment techniques in actual banking settings while resolving concerns about transparency, ethical compliance, and regulatory alignment is the scientific challenge this study attempts to solve.

The object of this research is the integration of artificial intelligence technologies into the risk management processes of banking institutions. AI's development as a revolutionary tool in a number of sectors, including finance:

Due to its capacity to provide highly automated and data-driven decision-making, AI is rapidly transforming the financial sector.

Literature review

Successful risk management is essential to banks' stability and financial success. It supports investor confidence, regulatory compliance, and asset protection. Inadequate risk management can lead to significant financial losses, penalties, and reputational damage. Integrating AI could enhance the accuracy, efficacy, and predictive capacity of risk management processes. Additionally, AI risk management can enhance an organization's overall decision-making process. Organizations can comprehensively know their risks by combining qualitative and quantitative evaluations, including statistical techniques and professional judgments (Lyeonov, 2024, p.326).

The authors of this work aims to comprehend how AI-based predictive financial modelling contributes to risk management, as demonstrated by market volatility, fraud identification, credit risk profiling, and compliance with established regulatory requirements. Through the implementation of artificial intelligence features, banking institutions can develop real-time risk models. AI also allows risk managers to focus on the high-level duties required to increase the risk resilience of financial organisations by assigning many of the manual chores. Additionally, the AI's ability to learn from massive data sources and analyse all types of sources is crucial since it improves risk prognosis reliability, removes human bias, and produces more accurate forecasts. Concerns including data privacy, the interpretability of AI models, and the issue of the legal frameworks controlling AI in banking are also covered in the study. According to the findings, AI has the ability to fundamentally alter ways the banking sector manages the risks required to operate in the current environment. AI has certain drawbacks despite its benefits in risk management and predictive financial modelling. Therefore, it is reasonable to list the following challenges: intelligibility, accessibility, and feasibility continue to be crucial difficulties, particularly in light of the so-called «black box» dilemma. Financial institutions and regulators also want us to provide an explanation for our decisions, particularly when it comes to credit risk identification and control or loan sanction. Privacy and data security remain major concerns (Vaithilingam, 2022). Bacause many AI systems work with large data sets, whose dependability is critical for sensitive financial data, it is necessary to focus on the secrecy issue. Concerns about data include how it is gathered, whether it is retained, and how it is utilised, particularly in light of the growing laws pertaining to data privacy. Fourthly, the integration of AI into the existing banking systems indicates that they must make investments in sufficient staff and infrastructure. Banks must either develop AI training internally or rely on outside AI service providers, such as fintech firms. Even so, there is a lot of hope for the future of AI in banking over the next five years, including increased regulatory compliance, model openness, and the broad use of AI-driven risk management (Mhlanga, 2021, p.39).

Overview of traditional risk management methods in banking:

Traditional banking risk management techniques are focus primarily on using established processes like loan underwriting rules to identify, assess, and mitigate specific, well-defined risks like credit risk, operational risk, and management risk (Belanche, 2019, p.1412). This is in contrast to current Enterprise Risk Management (ERM), which aims to control interrelated risks across the bank.

These methods are often compartmentalized, with different departments managing their own risks rather than taking a holistic view across the entire organization. A bank's trading activities are the primary source of market risk, whereas operational risk is the possibility of suffering losses due to internal system malfunctions or outside circumstances. Most big banks compute economic capital in addition to regulatory capital, which is determined by the bank's models rather than by regulators' recommendations (Nnaomah, 2024). In addition to liquidity, business, and reputational risks, banks are primarily exposed to credit, market, and operational risks. Banks actively participate in risk management to monitor, control, and quantify these risks (Hair, 2019,p.3).

Recent advances in AI techniques connected to risk management: Machine learning (ML), natural language processing (NLP), and predictive analytics are examples of recent advancements in Ai techniques which have rendered it possible for banks to detect potential hazards early.

Enhance your evaluation of complicated sets of data and take proactive steps to reduce risks. This is particularly significant to tracking market volatility, detecting fraud, and evaluating credit risk. Financial institutions that provide insurance services for various types of risk incur an important portion of the financial risks. For these businesses, it is vital to accurately estimate the exposure and take the necessary steps to lower these risks. For insurance, there are many different sources of financial risk, and each one demands reliable forecasting models. Considering the development of AI-driven optimization techniques, there are now more chances to enhance risk management.

Neural networks and SVM are two examples of machine learning algorithms that provide the capacity to examine enormous datasets and spot intricate patterns that conventional models could overlook. Banks can gain insights from unstructured data sources like news articles and social media using natural language processing or NLP. Reinforcement learning offers adaptive models that can gain knowledge from experience and gradually enhance risk management techniques. The potential of these methods to increase operational effectiveness and forecast accuracy is shown by research on AI-driven optimization in risk management. Studies have shown that machine learning models can perform better than conventional risk assessment techniques in several applications, such as credit scoring, fraud detection, and market risk prediction. However, data quality, model interpretability, and regulatory compliance challenges must also be addressed (El Hajj, & Hammoud, 2023, p. 434).

Exploration of AI applications in banking beyond risk management, such as loan underwriting, customer segmentation, and investment strategies:

Applications of AI in banking go beyond risk management. These include loan underwriting, where AI can analyze large data sets to make more accurate credit decisions; customer segmentation, which uses AI to classify customers based on their behaviors and needs for personalized offerings; and investment strategies, which use AI-powered robo-advisors to manage portfolios based on individual risk profiles as well as financial goals; fraud detection, chatbot-based personalized customer service, market trend analysis, and compliance monitoring. AI and ML have become essential weapons in the fight against financial crimes, including cybercrime and money laundering. Anti-money laundering (AML) procedures are given top priority by financial organizations to abide by laws and stop illegal activity (Ahmed, 2023, p. 13873). AI and ML methods increase efficiency and reduce manual involvement by automating the detection of questionable transactions. Additionally, by identifying trends in consumer behavior suggestive of fraudulent activities, these technologies make it possible to take preventative action. With the help of computer algorithms, algorithmic trading has become increasingly popular. In high-frequency trading, it is especially common. AI and ML are essential to creating complex algorithms that can analyze massive datasets and find patterns that are beyond human comprehension. This development reduces risk and improves trading performance.

The work focused on using AI and ML applications in financial management (Bouchetara, 2024, p.125). Their analysis, which looked at 283 scientific papers, highlighted how widely machine learning techniques are used. They mainly focused on asset pricing, fintech, and financial fraud in their proposed scope for further study. Nevertheless, they investigated access, financial technology, and financial services with a focus on fintech (Srivastava, 2024). These papers offer useful insights into the literature on fintech. They are not going to offer recommendations for BFSI research, though, and they don't cover every publication.

To frame the study conceptually, this research draws upon key theoretical approaches such as Enterprise Risk Management (ERM), which emphasizes integrated, organization-wide risk governance, and the information Processing Theory(IPT), which explains how AI enhances decision-making by increasing a system's capacity to process complex and large-scale information. These models help contextualize AI's value proposition in overcoming the limitations of traditional rule-based banking systems that are constraint by cognitive and structural rigidity.

The reviewed literature collectively supports the adoption of machine learning algorithms, such as Random Forest, XGBoost, and Gradient Boosting, in risk management processes, due to their superior performance in classification and prediction tasks.

The selection of mixed-method approach, including empirical modelling using Kaggle datasets and a regional survey of bank employees, reflects the need to both quantify model performance and capture institutional perceptions-bridging the gap between theoretical application and practical adoption. This alignment between theory and methodology enhances the academic robustness of the research and validates the relevance of the proposed AI-based framework.

Gaps in existing research

Most respondents predicted that AI and ML would have a positive effect on finance, frequently pointing to increased efficiency and accuracy. This is consistent with previous studies that highlight how AI and ML could transform financial services by streamlining processes, reducing expenses, and enhancing overall company performance. As professionals and firms attempt to use these techniques to obtain a competitive edge, these advantages may promote the growth and development of AI and ML applications in the financial sector (Rolando, 2024b,p.250). Participants expressed concerns about possible job losses and ethical and privacy issues brought on by AI and ML, notwithstanding this upbeat viewpoint. Task automation-related job loss is a common worry in AI and ML discussions, suggesting possible labor redundancies in various industries, including finance. Job loss is still a contentious topic among policymakers, practitioners, and academics, even though study participants did not view it as an imminent threat. When using AI and ML, significant consideration should be given to ethical and privacy issues, including bias in decision-making or unauthorized data access. Establishing appropriate laws and industry standards is essential to addressing these issues and guaranteeing the ethical and responsible application of AI and ML (Zhang, 2020,p.18).

The complexity of financial risk situations and the technical prowess of ensemble machine learning algorithms like XGBoost, Random Forest, and Gradient Boosting make them applicable in the banking sector. While helpful, traditional statistical techniques frequently struggle to handle data with high dimensions, unstructured information, and non-linear interactions- all of which are common in banking datasets used for compliance monitoring, fraud detection, and credit scoring. The ensemble learning techniques Random Forest and XGBoost are renowned for their excellent accuracy resistance to overfitting and ability to handle missing values. These qualities are vital when dealing with the frequently imbalanced or incomplete real-world banking data. In particular XGBoost learns complex trends and dependencies in the data by applying gradient boosting to decision trees. This ability is crucial for detecting subtle fraud trends and hidden risk indicators that linear models can miss. In the highly regulated banking sector where choices are frequently required to be explicable to auditors and compliance authorities, these algorithms also rank aspects based on their value, which enhances transparency and interpretability. Moreover, they are computationally efficient and scalable, which makes them appropriate for large-scale financial systems where automated decision-making and real-time risk assessment are becoming more and more crucial.

The employment of ensemble methods is theoretically supported by the bias-variance trade-off in machine learning. While boosting algorithms like XGBoost reduce bias by progressively correcting errors, techniques like Random Forest reduce variance by aggregating multiple trees. Because of this, they are highly suited for generalizability and prediction accuracy, especially in high-stakes financial settings where false positives and false negatives can result in substantial expenses.

Finally, empirical studies (e.g., Gautam 2023; El Hajj&Hammoud, 2023) have consistently demonstrated the superior performance of ensemble models in banking-related tasks. These results are consistent with theoretical frameworks from computational finance and decision science that highlight the value of high-dimensional, adaptive, and nonlinear analysis in contemporary risk management.

Methodology

The research goal of assessing how well AI-based solutions, in particular machine learning models, manage banking risks informs the study's methodological design. To achieve this, a mixed-method strategy was adopted that incorporates both descriptive and explanatory components.

The descriptive part of the study uses structured survey data from 200 bank employees in the Middle East to capture institutional perceptions, practical implementation status, and perceived barriers to AI adoption. This provides context and baseline insights into existing risk management practices and digital readiness.

The explanatory component involves technical evaluation of AI models using a real-world dataset from Kaggle, which allows for a controlled assessment of model accuracy, precision, recall, and F1 score. These metrics were selected due to their relevance in classification tasks central to credit risk and fraud detection-key focus areas of this research.

Specifically, models such as Random Forest, XGBoost, and AdaBoost were chosen based on their proven effectiveness in prior financial studies and their robustness in handling imbalanced datasets. The choice of this models is supported by their ability to detect complex non-linear relationships in multidimensional data, which traditional linear models fail to capture.

The research questions guiding this study include:

- How can machine learning models improve prediction accuracy in banking risk assessment?

- Which AI algorithms perform best in detecting credit risk and fraud using real data?
- What institutional and technical challenges hinder AI adoption in banking?

These questions directly informed the dual selection of survey and model analysis tools, ensuring methodological consistency and alignment with the study's overarching objectives.

Systematic fusion in risk management involves combining AI with traditional risk management techniques to improve risk assessment and decision-making. An AI-centered approach considering conventional risk management strategies will produce a more thorough and precise system. AI's ability to circumvent the drawbacks of conventional methods makes it a valuable addition to traditional risk management methods. Traditional risk management methods are synonymous with laborious, expensive, flawed physical labor and subjective judgments. Big data can be quickly and accurately interpreted by AI, which also offers data-based methodologies and a predictive strategy that differs from earlier techniques. Financial institutions will thus have a more exact and accurate method of risk detection, assessment, and mitigation thanks to this collaborative approach. The following steps make up a framework for combining AI augmentation with current risk management techniques (Table 1).

Table 1 – Steps of AI augmentation with current risk management techniques

Step	Description
Data Preparation and Collection	Financial institutions gather data from various sources like market research, internal audits, customer feedback, and regulatory changes.
AI Model Development	Machine-learning algorithms help financial organizations detect patterns, anomalies, correlations, and causal relationships in data.
Model Validation and Testing	AI techniques are assessed using evaluation metrics like F1 score, accuracy, precision, and recall.
Model Deployment and Monitoring	AI models are implemented in real-world scenarios, with continuous monitoring to ensure functionality.
Continuous Improvement	AI systems are regularly evaluated, updated with new data, and integrated with traditional approaches to enhance risk management, improve reporting, and protect data privacy.
Note – compiled by the authors based on the sources (Dewasiri, 2024, p.197)	

Notably, synergy involves combining AI with other conventional risk management techniques to generate a more thorough risk assessment and decision-making process. Financial organizations can apply an AI combination of current risk management methodologies to achieve accuracy and consistency in risk detection, assessment, and management. The research problem can be resolved more easily when an appropriate research approach is chosen for the investigation. Since this study is mostly quantitative, it used both descriptive and explanatory methodologies, which facilitate information gathering. Quantifiable data are used to better comprehend how different research variables affect to one another. A descriptive research methodology was selected for examining respondents demographic distribution and general opinions about the issue. This study used an innovative research technique which combined both deductive and inductive methods. The research approach enhances the study's credibility and serves as a guide for carrying out the investigation. A hybrid method was chosen to enhance the accuracy of research findings. The survey utilized to gather primary quantitative data from the respondents served as the foundation for the research strategy for this study. The survey approach was chosen to collect data from a big sample population – 200 bank employees from certain banks in the Middle East and a wide geographic area. A structured, closed-ended questionnaire was the research tool utilized in this study to gather quantitative data. They were contacted and polled to find out where AI is being used and how it affects the Middle Eastern banking industry's performance (Zhan, 2024, p.190).

Data Analysis:

The study is based on a secondary dataset from Kaggle. This dataset contains actual bank statistics provided on the internet after clients' sensitive personal information has been removed. There are two separate data files: application_record.csv and credit_record.csv. The first application record dataset contains the applicants' information, which can be used as predictive features. The second dataset, credit record, monitors consumers' credit card usage patterns (credit history). ID column (primary key) connects application and credit record datasets. The data was created by combining two tables linked by ID. The credit_record.csv file has three columns: client ID, record month, and customer status. To begin, record the month in which the data was collected. Moving backward, 0 indicates the current month, and -1 represents the previous month. The status column shows the following amounts as past due: 0: 1-29 days, 1: 30-59 days, 2: 60-89 days, 3: 90-119 days, 4: 120-149 days, and 5: write-offs for past-due or bad debts lasting more than 150 days. «C» denotes the month's payments, whereas «X» signifies no loan for the month.

Exploratory Data Analysis (EDA)

Raw data, often known as unprocessed data, is only helpful if there is something to learn from analyzing it. EDA entails analyzing and visually portraying data to acquire insights and summarising key data features to understand a dataset better.

According to IBM, EDA provides customers with a deeper understanding of variables in data collection and their relationships. It is typically used to investigate what data can be disclosed beyond the formal modeling or hypothesis testing assignments. EDA can also help determine whether the statistical procedures under consideration for the study methodology are adequate.

Some methods include many features, which can make layout and training processes more time-consuming and memory-intensive. Each feature must devote a significant amount of time and effort to scanning through the numerous data instances and estimating every potential split point, which is the fundamental cause of this behaviour. Fewer attributes are recommended to save time during the computing process and improve method performance. Table 2's summary statistics help better understand the variable distribution.

Results and discussions

When determining a borrower's credit score, credit scoring algorithms usually consider several variables, such as the borrower's history of on-time payments on prior obligations. The difference between the borrower's available credit limits and the amount of credit they have used. The duration of the borrower's credit usage. Variety of credit accounts, including mortgages, loans, and credit cards. how many people have recently checked a borrower's credit record? Lenders use various credit scoring methods to assess borrowers' creditworthiness for various credit applications. These models are customized for particular sectors, like mortgage or auto loans. Several lenders use specialized scoring models Depending on their lending requirements and risk tolerance. A company's financial performance and creditworthiness are calculated utilizing financial ratios, which are quantitative measurements from its financial statements. Financial measures like the debt-to-equity ratio and the debt service coverage ratio, which gauge a company's leverage and capacity to pay off its debts, are frequently employed in credit risk assessments. such as return on equity and return on assets, which show how profitable and effective the business produces returns, such as fast and current ratios, which calculate a business's capacity to pay short-term debts. The association between borrower attributes and credit risk is modeled using statistical methods like logistic regression and discriminant analysis. By examining past data, these methods find trends and connections that can be utilized to forecast the probability of default.

The console prints the results of the method calculation, including accuracy, F1 score, precision, recall, and confusion matrix, which provide useful insights into the effectiveness of the chosen ML method for loan approval prediction.

The base measure utilized for method calculations is frequently accuracy, which describes the number of correct predictions out of all forecasts:

$$\text{Accuracy=TN+TPTN+FP+FN+TP} \quad (1)$$

Next statistic is accuracy, which evaluates how many positive forecasts are correct (true positives):

$$\text{Precision= TPTP+FP} \quad (2)$$

Recall is a measure of how many positive cases the classifier properly predicts out of all positive examples in the data.

$$\text{Recall= TPTP+FN} \quad (3)$$

F1 score is a measure that combines precision and recall. It is commonly known as the harmonic mean of two:

$$\text{F1 Score=2} * \text{Precision} * \text{RecallPrecision+Recall} \quad (4)$$

Table 2 – Summary statistics of variables

Indicator	Count	Mean	Std.Dev	Min	25 %	50 %	75%	max
ID (Unique Identifier)	438557.000	6022176270	571637.023	$008804.000	$609975.000	6047745.000	6456971.000	7900062000
Number of Children	438557.000	0.427	0.725	0.000	0.000	0.000	1.000	10.000
Total Annual Income(KZT)	438557.000	187524.286	5 110066.853	26100.000	121500.000	160780.500	225000.000	6750000.000
Application Height(mm or score unit)	438557.000	+15007.905	4185.000	25201.000	19483.000	15630,000	12514.000	.7499.000
Applicant Weight (possibly income gap)	438557.000	60563.675	138767.800	17631.000	3103000	1467.000	.371.000	365243000
Marital status indicator (binary)	436567.000	51.000	0.000	-1.000	-1.000	- 1.000	1.000	1.000
Job status Indicator(employed/ unemployed)	439557.000	0206	0.405	0.000	0000	0.000	0.000	1,000
Home Ownership Indicator	438557.000	0.288	0.453	0.000	0.000	0.000	1,000	1.000
Education Level Indicator	438557.000	0.108	0.311	0.000	0.000	0.000	0.000	1.000
Number of Family Members	438557.000	2.194	0.897	1.000	2000	2000	3.000	20.000

Note – compiled by the authors based on the source (Naeem, 2025:84-91)

Confusion matrix visualization enabled a thorough examination of method classification accuracy and error rates. Algorithms were implemented in Python, and data processing was performed using well-known libraries such as Pandas, Numpy, and Sklearn. After loading the dataset, preprocessing was done to improve method efficacy, resulting in better results.

Additionally, computing resources should be considered, mainly when dealing with massive datasets. Some methods are computationally expensive. Therefore, their performance must be weighed against available resources. Analysis results should be interpreted with caution.

Multiple metrics generated from a confusion matrix are commonly used to measure the efficacy of a classification model. The confusion matrix summarises method performance by displaying four main metrics: true negatives (TNs), false positives (FPs), false negatives (FNs), and true positives (TPs).

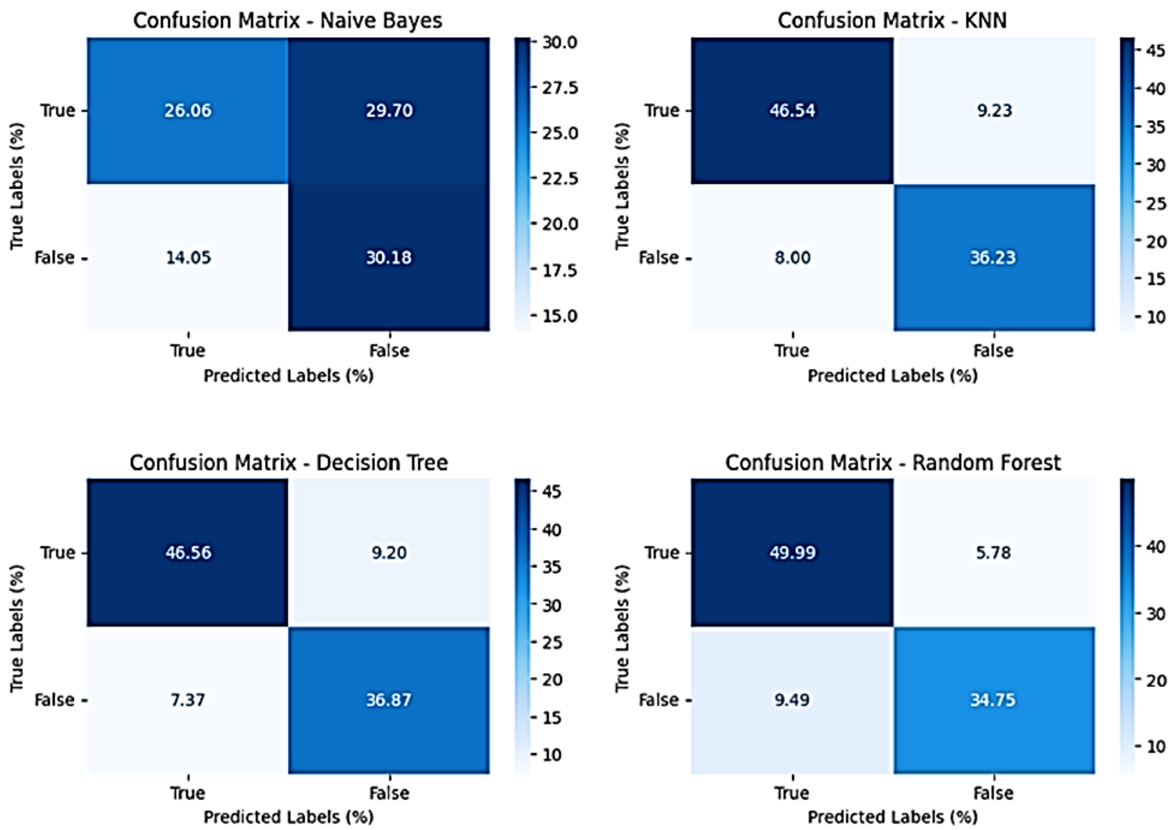

Figure 1 – Confusion matrix
Note – compiled by authors based on the source (Henseler, 2010:714-725)

Table 3 and Figure 1 show the findings of our analysis using the confusion matrix. The binary classification issue distinguishes between regular observations and observations with a specific outcome as shown in figure 1. According to our model's projections, the clients will either default on their debt or not.

This results in the following:

True positives occur when good consumers are correctly expected to be good customers.

False positive – when poor consumers are mistakenly identified as good ones.

True negative – when bad consumers are correctly expected to be bad clients.

False negative – when friendly consumers are mistakenly identified as bad customers.

The equations for calculating the respective rates are as follows:

Actual positive = Number of clients correctly projected as excellent / Actual number of good consumers

False positive = number of clients incorrectly projected as good/actual number of negative customers.

True negative = Number of clients correctly predicted as bad / Actual number of bad customers

False negative = number of consumers incorrectly forecasted as poor / actual number of excellent customers.

Test samples show that 7422 are excellent clients and 7406 are bad ones. Based on the number of real good and terrible clients for the prediction algorithm, we will compare FPR, TPR, FNR, and TNR for the best and worst-performing methods.

Table 3 – Confusion matrix results

	True Neg	False Pos	False Neg	True Pos
Naive Bayes	15.48%	78.17%	1.59%	4.76%
Random forest	1.59%	1.59%	15.48%	81.35%
Decision tree	3.97%	11.90%	13.10%	71.03%
KNN	1.19%	3.97%	15.87%	78.97%
AdaBoost	2.38%	4.37%	14.68%	78.57%
XGBoost	1.98%	1.19%	15.08%	81.75%
Gradient boost	3.17%	3.17%	13.89%	79.76%
Note – compiled by authors based on the source (Truby, 2022:272)				

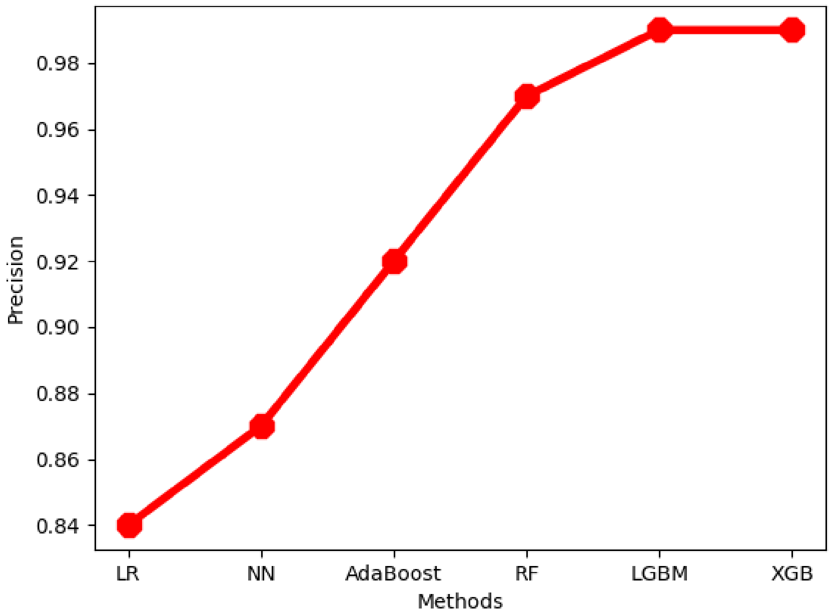

Figure 2 – Precision comparison
Note – compiled by authors based on the source (Waltman, 2019)

According to the accuracy and recall comparison bar charts in Figures 2 and 3, the model XGB has the best possible precision and recall (both 0.994), followed by the model LGBM (0.992 and 0.993). Furthermore, logistic regression has the lowest precision and recall scores (0.846 and 0.843, respectively).

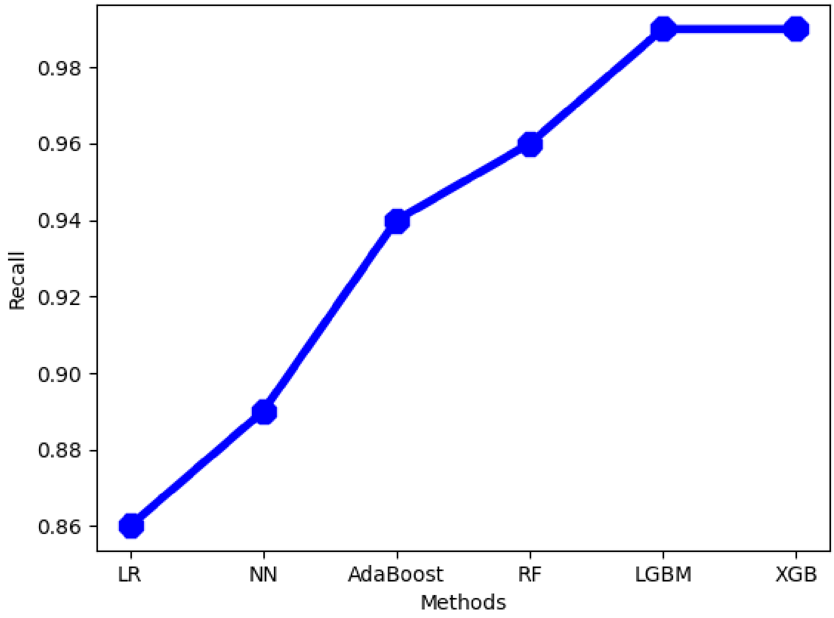

Figure 3 – Recall comparison
Note – compiled by authors based on the source (Waltman, 2019)

F1 Score

The F1 score represents a harmonic recall and precision average ranging from 0 to 1. For a binary classification task, optimizing for the F1 score is the most recommended quality metric. The overall performance of the method improves as the F1 score rises, with 0 being the lowest and 1 being the highest. Only when precision and recall are 100% can the F1 score reach its optimal level of 1. If one of these equals 0, the F1 score's worst value is zero.

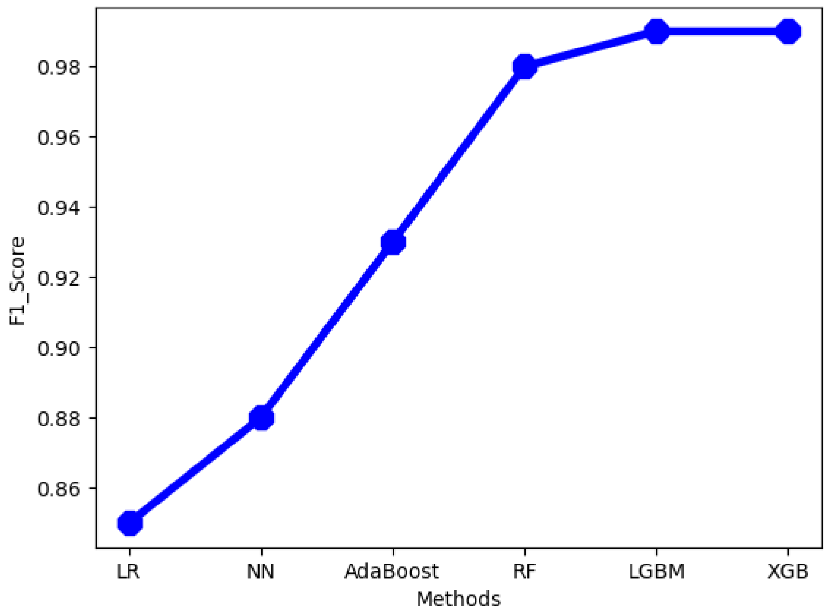

Figure 4 – F1 score
Note – compiled by authors based on the source (Vaithilingam, 2022)

Figure 4 reflects the scenario in the same way recall and precision were explained earlier. This shows that method XGB earns the best possible F1 score because it has the maximum recall and precision. Methods closer to the top left corner, corresponding to Cartesian plane coordinate (0, 1), perform better than those listed below.

The test will become less exact as the graph approaches the ROC plot's 45-degree diagonal. One of the many reasons the ROC curve is so useful is that it is independent of the class distribution. It permits and facilitates circumstances in which classifiers forecast odd events, corresponding to our interest in detecting undesirable consumers.

AUC values vary from zero to one. An AUC of 0 suggests a model with 100% erroneous predictions, whereas an AUC of 1 represents a method with all correct predictions. If the area under the curve (AUC) equals 0.5, we can deduce that the method is incapable of distinguishing between good as well as bad consumers properly.

On a ROC curve, a higher value on the x-axis indicates more false positives than true negatives. At the same time, a higher number on the y-axis indicates a greater proportion of TP vs FN. As a result, threshold selection depends on the ability to balance FP and FN. A comparison of random forest, neural networks, XGB, LGBM, AdaBoost, and logistic regression models is shown below. Figure 5 indicates that XGB and LGBM perform better.

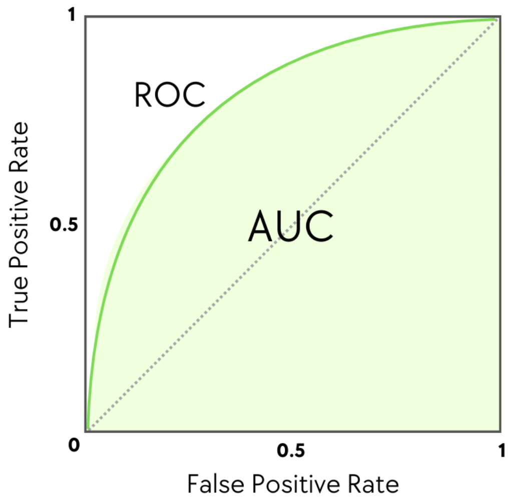

Figure 5 – ROC–AUC curve
Note – compiled by authors based on the source (Yao, 2023: 2777)

Economic Implications of Machine Learning in Credit Risk Assessment

Machine learning has altered credit risk assessment in the banking and finance industries by providing a data-driven method to evaluating borrower's creditworthiness. ML has significant fiscal consequences for the banking sector as well as to its technical promise. These include improved regulatory compliance and risk management, increased accuracy and predictive power, cost reductions, and efficiency gains.

This explores economic monetary effects by looking at how machine learning alters credit risk assessment processes and supports institutions stability and financial well-being. Increasingly accurate risk assessments are rendered practical by spotting little features and relationships that human researchers and traditional credit risk models night overlook. This tailored method improves the level of detail and accuracy of credit risk evaluations correctly matching loan terms and price to borrower's risk profiles, maximizing risk-adjusted earnings and minimizing credit losses.

In credit risk assessment, fraud detection and prevention involves employing advanced data analytics and monitoring technologies to spot suspicious trends and activities in credit transactions or loan applications. This aims to reduce financial losses for lenders and actively stop fraudulent activity before a loan is granted. Putting a system in place to recognize and evaluate possible risks and stop illicit transactions before they are completed is the most efficient way to avoid fraud. Numerous risk management technologies, including transaction pattern analysis and advanced data analytics, should be integrated in a thorough fraud detection system.

Detecting financial fraud is a set of methods and procedures designed to reduce risk. Scammers frequently target financial institutions because they may transfer money and have instant access. Bank fraud issues can be broadly categorized into three categories:

Customer Onboarding

Regulations like KYC (know your customer) and AML (anti-money laundering) make digital onboarding, a component of customer acquisition, problematic for banks. Using customer risk assessment, these regulatory criteria verify user identities and ensure they won't commit financial crimes. Scammers use phony or synthetic identification documents to trick the system and open bank accounts. In 2020, the cost of ID verification is expected to reach $35.2 billion. It's particularly challenging for challenger banks and neobanks, which must quickly and effortlessly attract new clients.

Credit card prevention

To successfully avoid credit card fraud, issuing organizations should be informed of any unusual transactions or withdrawals. Because they only have access to the merchant's name, category, amount, and currency, it is difficult to spot trends. If they try to use these criteria to block fraudulent payments, they run the danger of creating high false positive rates, which would irritate responsible cardholders. Other regulatory criteria involve validating the legitimacy of the financing source and using Strong customer Authentication (SCA).

Account protection

An account takeover (ATO) takes place when hackers manage to get their hands on an actual user's login credentials. They use the account as their own, which has a terrible impact on bank's connections with their customers. In addition to allowing other types of fraud and criminal conduct. Banks must therefore take every safety measure to protect the accounts of their clients.

Naturally, the larger issue is that fraud is adaptive. In other words, when their activities are restricted, scammers will swiftly realize and try a different strategy. Solutions like AML software and KYC technologies must be effective and adaptable.

Regulatory compliance and reporting

Financial institutions' risk management teams invest significant time and money in obtaining and tracking data about various risk factors, including transaction restrictions, exposure limitations, regulatory constraints, and so forth. Furthermore, risk reporting has become a strategic function due to the constantly changing regulatory standards and increased management attention to risk management. Even while technology is essential to running these activities, having a sizable staff of risk analysts committed to ad hoc reporting and routine risk monitoring has become essential (Umamaheswari, 2023, pp. 2841-2849).

In the banking industry, artificial intelligence (AI) is being used to reduce a growing number of risks, such as credit and market risks, transaction risks, model risks, cybersecurity risks, infection risks, and compliance risks (Table 4).

Table 4 – Risks in the banking sector

Risk type	Description
Credit risk	The possible loss that results from loan default by counterparties or borrowers.
Market risk	Financial markets' volatility poses a serious threat to banks' bottom lines. AI techniques like machine learning, deep learning, and natural language processing are used to forecast trends and enhance decision-making.
Operational risk	Includes losses due to system breaches, service interruptions, or failures in internal systems and processes.
Model risk	Banks rely on various models to forecast and plan their operations, but flaws in these models can introduce risks.
Cybersecurity risk	The growing number of attack vectors in an interconnected world poses cybersecurity threats. AI-driven machine learning and deep learning detect anomalies, predict attacker behavior, and mitigate risks.
Contagion risk	Economic disruptions, such as the global impact of COVID-19 or financial collapses in foreign markets, can affect banking operations and existing loan arrangements.
Compliance risk	If banks fail to comply with regulations, they may face financial loss, legal consequences, or reputational damage. Regulatory compliance is an ongoing and complex challenge.
Note – compiled by the authors based on the sources (Ahmed, 2023).	

AI significantly affects contemporary sectors like manufacturing, retail, healthcare, and finance. Repetitive operations could be replaced, vast amounts of data could be analyzed to gain insights, processes could be optimized, decision-making could be enhanced, and adopted consumer experiences could be provided. Ultimately, this results in improved creativity and operational efficiency.

Conclusion

By improving the precision and effectiveness of several procedures, including fraud detection and credit risk assessment, machine learning (ML) has profoundly transformed the banking sector.

The application of AI and ML in the banking industry has attracted a lot of attention in recent years. The objective of this paper is to present a thorough evaluation of the corpus of research on the application of AI-based risk management in the banking sector. This study used a desk methodological approach to compile the development and use of AI in financial risk management.

This investigation is unique because it integrates qualitative survey data from a geographically specific banking population (the Middle East) with real-world banking datasets and sophisticated machine learning techniques. In contrast to previous research, which frequently concentrates only on theoretical models or regionally isolated applications, this work uses ensemble models and evaluates comparative performance using confusion matrices, ROC curves, and F1 scores.

The suggested method has a lot of potential for use in Kazakhstan and other CIS nations, where banking systems are rapidly moving digital but still have issues with legacy infrastructure and regulatory adaption. Local banks can improve their credit scoring processes by using XGBoost and Random Forest models, especially in high-risk or underserved borrower sectors where traditional scoring models and imprecise. Additionally, incorporating AI into fraud detection systems can provide real-time transaction monitoring, which is crucial for reducing the region's growing cyberthreats.

The suggested AI framework could be used practically by Kazakhstani commercial banks to enhance compliance reporting through automated anomaly detection, decrease false positives in anti-money laundering (AML) systems, and streamline loan approval processes in online banking platforms. In addition to improving operational effectiveness, these applications would boost regulator and customer trust.

Despite its advantages, using machine learning in the financial sector comes with a number of risks and challenges. Sensitive data is essential in the financial sector. Because financial institutions handle vast amounts of transactional and personal data, data security and privacy are essential. Serious consequences, including financial loss, penalties, and reputational damage, can result from data security breaches. Financial data sometimes contains very sensitive information, such as personal identification numbers, transaction histories, and bank account numbers. Preventing unwanted access to this data is one of the main obstacles. Removing personally identifiable information (PII) from datasets can lessen privacy risks while allowing data analysis. In the financial sector, it is crucial to comprehend and explain ML model decisions.

As the banking industry develops further, artificial intelligence's contribution to risk management will be crucial to maintaining stability and growth in a setting that is becoming more and more competitive. In the banking industry, risk management is a crucial field that encompasses a variety of procedures meant to detect, assess, an lessen possible unforeseen circumstances that can have a detrimental impact on the institution's operational stability and financial health.

The paper's key findings and observations demonstrate how AI optimization and methodology could be revolutionary components of banking risk management systems in the future. Banks may use AI algorithms to access the most comprehensive data sources, perform risk assessments, fraud detection, predictive analytics, real-time monitoring and warnings, and make the right decisions. AI can improve the accuracy, speed, and efficiency of risk management, which will ultimately lead to a more successful risk management strategy. Executing the plans of increasingly digital bank institutions requires a shift from analog to risk management. Making the most of blockchain technology and artificial intelligence is one of the most important phases in this process.

In turn, artificial intelligence makes it possible to process massive amounts of unstructured data risk, create appropriate models for evaluating market risk, fully automate manual processes in the function, more precisely identify future issues, and computerize credit scoring. AI risk management aids banks in better understanding and reducing risk. Banks may swiftly uncover insights that help them halt losses and increase their customer's return on investment by analyzing large amounts of data thanks to artificial intelligence (AI). AI is being used in the banking sector to counter a growing variety of dangers.

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