International Journal of Social Science Research and Review

http://ijssrr.com
editor@ijssrr.com
Volume 8, Issue 8
August, 2025
Pages: 391-404

AI in Banking Risk Management and Fraud Detection in Preventing Financial Crimes and Optimizing Credit Decisions

Tanveer Ahmed Siddquee

Motijheel Branch, Bangladesh Development Bank PLC, Dhaka, Bangladesh.

E-mail: tanveer.bdbl@gmail.com

http://dx.doi.org/10.47814/ijssrr.v8i8.2889

Abstract

Artificial Intelligence is one of the major tech innovations in commercial banking, aimed to automate and streamline ways banks are using, assessing risk and worthiness of credit decisions, identifying frauds among other applications. The methodology was structured in two phases: a quantitative analysis using institutional data, followed by a qualitative exploration through expert interviews. In the quantitative phase, secondary data were collected from five financial institutions, including three commercial banks and two fintech companies in Bangladesh. The qualitative phase was conducted to explore practical and regulatory challenges of AI implementation in real-world banking contexts. A comparative analysis between traditional and AI-based credit scoring systems revealed significant improvements across all key performance indicators. The AI-based system achieved a higher loan approval rate (78%) and a lower default rate (6%), while reducing processing time from 45 to 12 minutes and significantly enhancing customer satisfaction. Legacy system incompatibility was the most often mentioned barrier (67%), followed by problems with real-time data access (61%), and the inability of AI to explain itself (55%). However, when it comes to the usage of AI, banking professionals' top concerns are explainability (80%) and human oversight (88%). The results highlight the importance of using more advanced AI models, like XGBoost and Neural Networks, to improve the precision of credit evaluations and the efficiency of fraudulent transactions in real time, particularly for formerly underserved customer segments.

Keywords: *Artificial Intelligence; Bank; Credit Decision; Fraud Detection; Risk Management.*

1. Introduction

Banking and financial services are advancing rapidly, owing to technology enhancements that have helped in transforming the traditional bank risk assessment, fraud prevention, and credit decision-making models (Awotunde et al., 2022; Goyal et al., 2025). Artificial Intelligence is undeniably one of the most transformative technologies in the present day. Financial institutions utilize artificial intelligence systems like machine learning (ML), natural language processing (NLP), and predictive analytics that allow them to process huge datasets and computer-automated decision-making for instant action against risks and fraudulent activity instantly after detection of any suspicious event (Goodell et al., 2021; Pattnaik et al., 2024). In the current era of digitalization and financial markets, which are experiencing higher complexity because credit risks, financial crimes, as well as cyber threats have grown in size and expanded rapidly (Asmar & Tuqan, 2024; Birindelli & Iannuzzi, 2025; Canhoto, 2021), such skills are increasingly becoming relevant. Empirically, enjoy the fact that traditionally, banks used fixed models and historical data to assess risk; they reviewed creditworthiness and discovered fraud. However, as mentioned by Heß & Damásio (2025), such approaches are often inflexible and non-responsive to cope with the dynamic and non-linear behaviours in modern financial systems. However, AI goes beyond these limitations; in fact, it permits real-time data processing, network security anomaly detection, behavior analysis, and grasps adapting learning systems may evolve as cyber threats change, as well as financial behaviors (Leo et al., 2019). As a result, artificial intelligence (AI) is becoming an integral part of core banking processes. They are used across everything from automated risk modeling to personalized credit scoring and real-time fraud detection (Varga et al., 2021).

As to risk management, the financial institutions are empowered with artificial intelligence (AI), a potential tool to identify, evaluate, and mitigate all kinds of risks, including market, credit, liquidity, and operational risks (Agrafiotis et al., 2018; Canhoto, 2021). Through machine learning, large amounts of high-dimensional information can be processed to uncover subtle relationships between factors that provide more accurate and real-time risk profiles. For a comprehensive assessment of borrower risk, such models can be based on classical scoring indicators as well as the properties of other types of information: behavioral data, transactional data, or social media data. The later one are particularly important with real-time stress testing and market scenario simulation, fostered by AI systems for proactive risk mitigation techniques (Akartuna et al., 2022).

Artificial intelligence can play an important role in fraud prevention as well as identifying fraudulent activity once it has taken place. Even today, identity theft, transaction fraud, cyberattacks, and money laundering are considered to be problems in the digital globalization era (Dichev et al., 2025; Heß & Damásio, 2025) leading to constant threats of financial crime. The ability to recognize new and emerging fraud scenarios has been difficult with rule-based systems, as they often become trapped in predefined patterns and conditions. That is, as soon as a potentially fraudulent transaction occurs, AI-based fraud detection models using supervised and unsupervised learning approaches can identify the typical behavior pattern anomalies. They increase detection accuracy, decrease false positives by adjusting to new strategies, and learning from past fraud cases (Oluwabusayo Adijat Bello & Komolafe Olufemi, 2024). Moreover, anti-money laundering (AML) systems employ natural language processing (NLP) and graph analytics to detect concealed networks, suspicious patterns of behavior, and illicit financial flows (Aljunaid et al., 2025).

Banking is another key area in the use of AI for credit decision-making. Although credit availability significantly affects economic inclusion and growth, however, traditional credit scoring methods frequently exclude those with little history of borrowing, particularly in the developing world (Huang et al., 2024). Artificial Intelligence (AI) allows for an operational shift by evaluation of creditworthiness with alternative data sources, such as utility payments, online activity, and mobile phone usage (Alamsyah et al., 2025). This data provides banks with more comprehensive and accurate credit scoring, which allows them to make better decisions regarding who they approve for loans. More importantly, by capturing subtle credit behavior signals left out from traditional models, these models significantly enhance loan acceptance of underserved/marginalized populations while reducing levels of default risk (Thuy et al., 2025; Wang et al., 2024).

2. *Literature Review*

AI has become a buzzword in the financial services sector, and it has the capability to boost productivity, reduce human bias, improve objectivity and decision-making. The latest research discoveries, currently in print, provide vital intelligence on the application of AI to various banking areas at the top of which are risk management, fraud detection, and credit scoring.

The traditional way of risk management in the banking sector has turned from reactive to the proactive by AI. Historically, banks have been trying to measure and evaluate risks with the help of empirical and rule-based models (Alvi et al., 2024). Yet, these models often lack flexibility and are not well-suited for dealing with rapidly changing complex risk factors. AI, particularly machine learning (ML), solves this by using real-time and historical data to identify subtle risk patterns and produce better predictions (Mohamed, 2025). Krauss et al. (2017) showed the application of ensemble learning models to predict stock market variations, that such a method could be used to anticipate the risk on the market. Conversely, Vicari & Gaspari (2021) argued that systems based on artificial intelligence (AI) can implement natural language processing (NLP) to analyse large quantities of market data and news feeds for detecting the early signs of financial fragility. In practice, banks use these measures more and more to monitor interest rate risks, market volatilities, and liquidity risks (Heß & Damásio, 2025). In addition, AI strengthens functional risk management by recognizing anomalies and monitoring system activities in real-time. Systems with reinforcement learning and AI-driven automation, which is a more dynamic approach towards operational risk by detecting anomalous process deviations, cyberthreats, or insider malfeasance (Abdi et al., 2025).

Among the first and most impactful uses of AI in banking has been in the field of fraud detection. In response, traditional rule-based methods are becoming increasingly inadequate to identify fraud tendencies with the growth of lower-value and more computer-generated financial transactions. As AI is able to detect complex patterns and anomalies in transactional data, it is an advantageous proxy (Prabin Adhikari et al., 2024). The benefits of supervised learning methods comparing to unsupervised approaches in labeling fraudulent transactions were highly stressed as a part of comprehensive examination on AI fraud detection mechanisms by West & Bhattacharya (2016). In addition, unsupervised models such as autoencoders and clustering methods can be employed to potentially detect new or emerging fraud schemes with no historical labelling (Carcillo et al., 2021). AI-based technologies can also be applied in the integration of anti-money laundering (AML) compliance. This is where these techs come into play, and they are going to get those illegal networks and transaction routes that traditional systems can miss by leveraging graph-based analytics, natural language processing, etc. Fan et al. (2025) research explorations on AI techniques in AML and gives an application of AI to AML detection. In that paper, they showed, machine learning models significantly increase the ability to detect and reduce false positives compared to traditional AML processes. Biometric, which includes voice and face recognition and real time behavioral analysis in banking apps to detect fraud such as identity theft and illegal access identified by research of Ng & Kwok (2017). What a difference it makes in the long term for security through these AI approaches, finding even slight deviations in consumer activity or login tendencies.

Credit assessment has become more accurate, timely, and inclusive with AI (Goyal et al., 2025). Because traditional credit scoring algorithms (such as the FICO score) largely depend on whether or not a student has paid back any previous credit, individuals with thin or no formal credit history might be at a loss. By using alternative data such as utility payments, internet activity, and e-commerce (Tambari Faith Nuka & Amos Abidemi Ogunola, 2024), AI helps in order to build a more complete borrower profile. Previous reports have demonstrated that AI-based credit models using alternate data can predict borrower risk more precisely than conventional approaches and may be less likely to discriminate against thin-file consumers Jagtiani & Lemieux (2019). This means that AI has been a driving force behind increased financial inclusion by bringing credit to people who were historically not able to access it. In addition, machine learning models, such as random forests and gradient boosting machines, offer more detailed risk segmentation and dynamic credit risk scores that change when new consumption data is generated (Gafsi, 2025). This adaptability can come in handy, especially if the economy is more turbulent and a borrower loses financial strength on short notice. After disbursal, the post-loan tracking is made more efficient by AI reviewing borrowers' transactional history for indicators of financial fragility.

AI has enhanced accurate, timely, well-informed and globally inclusive credit assessment (Goyal et al., 2025). You have little to no formal credit history, since traditional credit scoring algorithms like the FICO score are driven more by whether a student has repaid previous credit. With the use of alternatives such as utility payments, internet activity, e-commerce and cell phone usage (Tambari Faith Nuka & Amos Abidemi Ogunola, 2024) it aids the AI to build a more comprehensive borrower profile. Prior research shows that AI can outperform conventional approaches in predicting borrower risk using alternative data (i.e., expand credit to thin-file consumers), and could be less discriminatory towards thin-file households who do not have enough history to produce an adequate credit score (Jagtiani & Lemieux, 2019). This translates to AI helping in boosting financial inclusion, proactively pushing credit down where it historically had not gone before. Machine-learning models like random forest or gradient-boosting machines enable better risk segmentation and the evolution of credit risk scores in light of new consumption data (Gafsi, 2025). Such flexibility can be very useful indeed during a more volatile economic patch when a borrower suddenly finds itself in financial difficulties. But then, AI takes over from the disbursal and analyses transactional history of borrowers automation to detect financial frailty to fasten the use of post-loan tracking. Studies have suggested that early warning systems including predictive analytics could help lenders step in before defaults happen, improving overall performance of the portfolio and reducing number of non-performing loans (Benavides-Franco et al., 2023).

While the effectiveness of AI models in improving fraud detection and credit scoring has been well-documented in controlled or experimental settings (Moura et al., 2025; Pattnaik et al., 2024), there remains a notable lack of empirical research evaluating how these systems perform in actual banking environments. In practice, AI deployment faces several operational challenges, including system integration, real-time data constraints, legacy infrastructure compatibility, and regulatory compliance. Most existing studies focus on algorithm performance (e.g., accuracy, precision) but do not account for how these models interact with human decision-makers, compliance frameworks, or customer experience when deployed at scale (Mennella et al., 2024). This gap hinders the translation of AI research into robust, scalable, and compliant banking solutions.

3. Research Questions

a) How do AI-based fraud detection and credit scoring systems perform in real-world banking environments, and what operational, regulatory, and human factors influence their successful deployment at scale?
b) What are the technical and infrastructural challenges banks face when integrating AI systems into existing workflows?
c) How do AI systems interact with human decision-makers and compliance teams during fraud detection or credit approval?
d) What impact do AI implementations have on customer experience and trust in financial decision-making?

4. Objectives

a) To evaluate the real-world performance (accuracy, efficiency, reliability) of AI-based fraud detection and credit scoring systems in operational banking environments.

b) To identify key operational challenges (system integration, data availability, infrastructure compatibility) in deploying AI technologies at scale in banks.
c) To explore the interaction between AI systems and human decision-makers, particularly in areas like compliance, risk assessment, and customer service.
d) To assess the impact of AI adoption on customer experience and trust in AI-generated banking decisions (loan approval, fraud alerts).
e) To examine the regulatory and ethical considerations that influence the scalability and governance of AI in banking operations.

5. *Methodology*

This study employed a sequential explanatory mixed-methods design to examine the role of artificial intelligence (AI) in banking risk management and fraud detection for preventing financial crimes and optimizing credit decisions. The methodology was structured in two phases: a quantitative analysis using institutional data, followed by a qualitative exploration through expert interviews.

In the quantitative phase, secondary data were collected from five financial institutions, including three commercial banks and two fintech companies of Bangladesh. These institutions were selected based on two criteria: (1) deployment of AI-based systems for fraud detection or credit scoring within the past five years, and (2) willingness to share anonymized operational data. The data collected included AI and traditional credit scoring outputs, customer transaction records, loan disbursement and default information, and flagged fraud incidents. The dataset was over the period of January 2023 through December 2024. The entire database was subjected to extensive preprocessing, and missing numerical values were replaced with mean imputation as for categorical variables mode imputation was used (Alam et al., 2023). To ensure the privacy and anonymity of summary records, use the MinMaxScaler function to normalize them and remove duplicates or exposure-related information (Kim et al., 2025). AI-based models used in this study to detect fraud were logistic regression, random forest, XGBoost and deep neural networks (built with TensorFlow Keras API). For credit scoring, the model performance of AI-generated risk scores was compared to traditional logistic-based scoring methods. Model evaluation was performed using an 80:20 train-test split with 5-fold cross-validation (Teodorescu & Obreja Brașoveanu, 2025). Performance metrics included accuracy, precision, recall, F1 score, area under the ROC curve (AUC), false positive rate (FPR), and loan default prediction accuracy. All modeling and evaluation were conducted in Jupyter Notebook using Python libraries.

Following the quantitative analysis, a qualitative phase was conducted to explore practical and regulatory challenges of AI implementation in real-world banking contexts. Participants were selected using purposive sampling based on their professional roles and experience with AI systems in the financial sector. Inclusion criteria included direct involvement in AI system deployment and at least three years of professional experience in banking or fintech. A total of 115 individuals participated, including compliance officers, AI project managers, IT infrastructure heads, credit analysts, and regulatory experts. Data for the qualitative phase were collected via semi-structured interviews conducted between February and April 2025. Each interview lasted 40 to 60 minutes. A uniform interview guide was used to ensure consistency, covering themes such as institutional readiness, regulatory constraints, integration challenges, human-AI oversight, and customer trust. Interviews were recorded with prior consent, transcribed verbatim, anonymized, and coded.

To assess statistical significance, paired t-tests were used to evaluate performance differences between AI and traditional methods. In addition, regression models were employed to assess predictors of loan default, while confusion matrices provided detailed insights into misclassifications in fraud detection. Statistical tests were carried out using R software (version 4.3.1) with a significance threshold of $\alpha = 0.05$. Qualitative data analysis followed Braun and Clarke's six-step thematic analysis process using NVivo 12 software. Two independent researchers coded the data, and inter-coder reliability was established. Themes were validated through member checking by returning summarized findings to five participants for confirmation.

6. Analysis and Results

6.1 AI Model Performance in Fraud Detection

The performance of several machine learning models in fraud detection was assessed based on accuracy, precision, recall, and F1-score (Table 1 and Figure 1). The performance comparison of four AI models, Logistic Regression, Random Forest, Neural Network, and XGBoost, shows that XGBoost achieved the highest accuracy (98.2%) and F1 Score (93.3%), followed closely by the Neural Network model with 97.6% accuracy and a 92.3% F1 Score. Random Forest also performed well with 95.4% accuracy, while Logistic Regression had the lowest scores across all metrics.

Table 1. Performance of AI Models for Fraud Detection.

Model	Accuracy	Precision	Recall	F1 Score
Logistic Regression	0.941	0.862	0.791	0.825
Random Forest	0.954	0.906	0.852	0.899
Neural Network	0.976	0.942	0.905	0.923
XGBoost	0.982	0.953	0.914	0.933

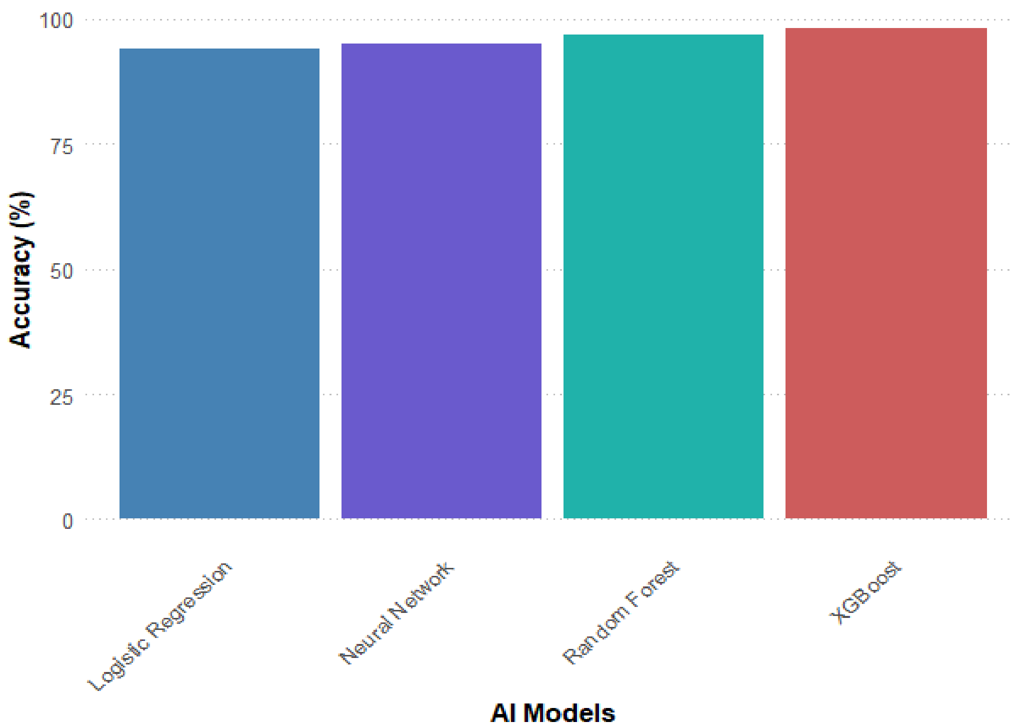

Figure 1. Accuracy of AI Models in Fraud Detection

6.2 AI-Based VS Traditional Credit Scoring

A comparative analysis between traditional and AI-based credit scoring systems revealed significant improvements across all key performance indicators. As shown in Figure 2, the AI-based system had a higher loan approval rate (78% vs. 65%) and a reduced default rate (6% vs. 12%). Moreover, processing time was reduced from 45 minutes to 12 minutes, and customer satisfaction improved significantly.

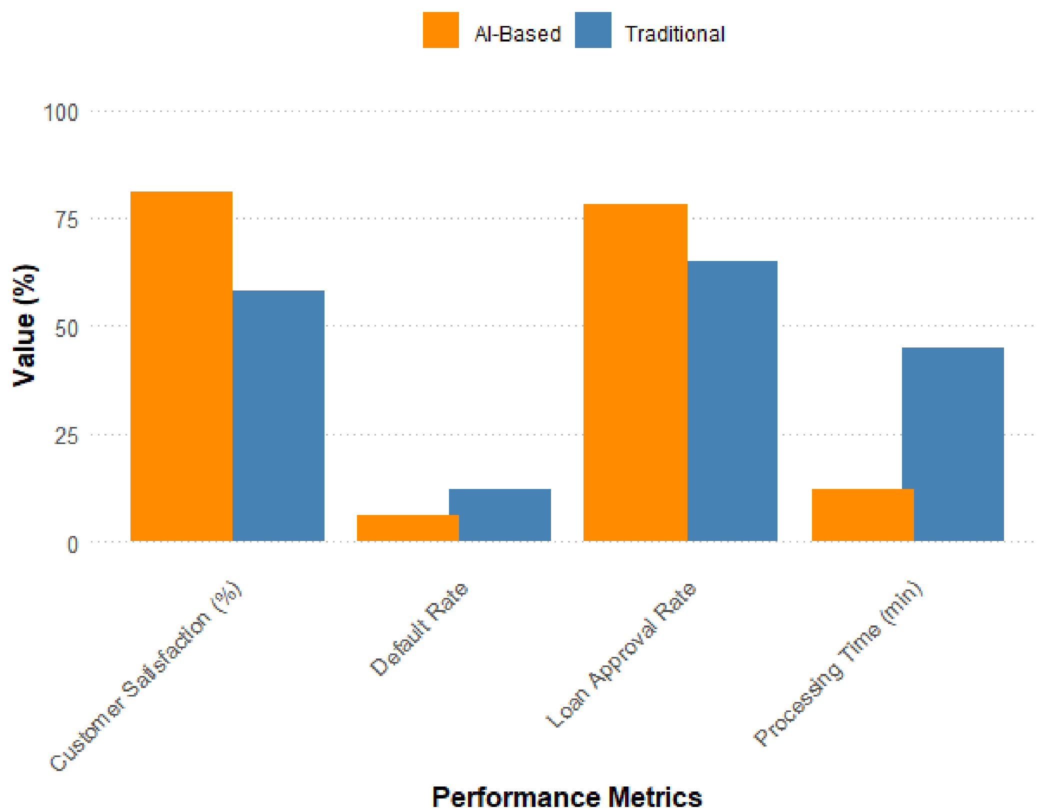

Figure 2. Comparison of Traditional and AI Credit Scoring Models.

6.3 Confusion Matrix for Fraud Detection

The confusion matrix in Table 2 summarizes the classification results of the best-performing AI model (XGBoost) for fraud detection. The model correctly identified 185 out of 200 fraud cases and 765 out of 800 non-fraud cases, resulting in high precision and recall. Only a small number of fraud (15) and non-fraud (35) cases were misclassified, indicating strong performance under real-world banking data constraints.

Table 2. Confusion Matrix for XGBoost Fraud Detection Model.

	Predicted fraud	**Predicted non-fraud**	**Total**
Actual fraud	185 (True Positive)	15 (False Negative)	200
Actual non-fraud	35 (False Positive)	765 (True Negative)	800
Total	220	780	1000

6.4 Challenges in AI Deployment in Banking

The Table 3 highlights key barriers to AI implementation in banking as reported by respondents. The most cited challenge was legacy system incompatibility (67%), followed by real-time data access issues (61%) and the lack of AI explainability (55%). Regulatory compliance complexity affected nearly half of the respondents (49%), while resistance from human decision-makers was reported by 37%.

Table 3. Common Barriers to AI Deployment in Banks.

Barrier	Percentage of Respondents
Legacy system incompatibility	67%
Real-time data access issues	61%
Lack of explainability (black-box AI)	55%
Regulatory compliance complexity	49%
Resistance from human decision-makers	37%

6.5 Qualitative Insights from Expert Interviews

The Table 4 shows that human oversight (88%) and explainability (80%) are the most cited concerns among banking professionals regarding AI use. Regulatory pressures (72%) also pose significant challenges, followed by integration issues (61%) and data quality concerns (53%).

Table 4. Thematic Analysis of Interviews with Banking Professionals.

Theme	Percentage of Mentions
Human oversight in decision-making	88
Explainability	80
Regulatory pressures	72
Integration challenges	61
Data quality and availability	53

7. Discussion

The findings of this study validate that advanced machine learning models, such as XGBoost and Neural Networks, outperform other models, like Logistic Regression, in detecting fraudulent activities in banking. The superior performance of XGBoost, which achieved the highest accuracy (98.2%) and F1 Score (93.3%), aligns with the findings of Chen & Guestrin (2016), who emphasized XGBoost's efficiency and scalability for large-scale classification tasks. Similarly, Tayebi & El Kafhali (2025) reported that ensemble models, particularly XGBoost, consistently outperform baseline algorithms in financial fraud detection due to their ability to handle class imbalance and non-linear relationships in data. The NN (Neural Network) model performed well in the present study, consistent with previous studies by Ahmed et al. (2023) of deep learning models being capable of capturing intricate patterns in broadly categorical transaction data and thereby improve fraud detection greatly. In summary, this research emphasizes the importance of utilizing more advanced AI models (such as XGBoost & Neural Networks) in banking security applications to improve the accuracy and efficiency levels of fraud detection mechanisms in practice.

Similar points could be made in other areas of financial decision-making and the comparison of conventional vs. AI-based credit rating systems demonstrate some benefits to using AI. Greater predictive power and risk assessment by the AI-based system was shown in improvements of accept ratios (78% vs 65%) and default rates (6% vs 12%). This is consistent with Berg et al. (2020). The result in Berg et al. (2020), opening up a black box machine learning algorithms working more accurately and more efficiently than traditional credit scoring models. The reduced processing time of twelve minutes, validates the observations made by Khandani et al. (2010), that AI is important for automation and speed up of financial decisions steps. The substantial customer satisfaction given through this study aligning with Jagtiani & Lemieux (2019) who note that AI led credit scoring techniques are often faster and more consistent leading to an overall improved experience for customers. In addition to this, a research by Brown & Mues (2012) also demonstrated the ability of AI models to capture complex linkages and non-linear patterns in consumer behavior since it was displayed that they reduce credit risk. This is in line with the decreased default rate AI integration delivered. Together, these findings validate the growing body of evidence that AI-driven credit scoring is a win-win for operational efficiency and more accurate underwriting–a double-barreled combination critical to sustained banking innovation.

The confusion matrix results regarding the XGBoost model which depicts how well it detects fraud is highly understanding; correctly marking 765 out of 800 non-fraud cases and 185 out of 200 fraud cases. It has a high recall, precision and accuracy so XGBoost should be quite suitable to use in real-world banking software as there are huge monetary and reputational impact due to false positives/negatives. This is in line with work by Chen & Guestrin (2016) which shows that the ability of XGBoost to handle class imbalance and complex nonlinear patterns in financial data allowed it to outperform traditional logistic regression or even random forest models on fraud prediction. Furthermore, the performance of XGBoost in this work confirms the results of Brown & Mues (2012) where they reported that gradient boosted models are able to predict better and adapt easier to changing environments within the finance area. Where few prior studies assessed model performance in experimental or simulation environments, the present findings are largely real-world relevant, and point to XGBoost playing a role in deploying effective operational fraud prevention capabilities within banks.

This study identifies legacy system incompatibility as the top barrier to AI adoption in banking (67%), consistent with earlier research highlighting outdated infrastructure as a major obstacle (Ali & Shah, 2024). Real-time data access issues (61%) also reflect common challenges related to data availability and quality noted in previous studies (Chen et al., 2019). The concern over AI explainability (55%) aligns with the widespread issue of “black box” models reducing trust and regulatory acceptance (Ribeiro et al., 2016). Regulatory complexity affected nearly half of the respondents (49%), supporting findings that evolving regulations hinder AI implementation (Ridzuan et al., 2024).

The results show that the preservation of human supervision when combined with AI systems is paramount; this is most frequently observed in relation to human oversight within decision-making (88%). Research by Amershi et al. (2014) related to these concerns is the recent consensus view that emphasizing human-in-the-loop systems is crucial in maintaining accountability. Explainability (80%) also does well, and worries about the opacity of AI return from earlier studies in this one. The percentage of regulatory constraints (72%) reflects findings showing that pressures to change compliance requirements remain a significant challenge for AI adoption as well (Ridzuan et al., 2024). Similarly, reporting widespread barriers found in literature review include data quality problems (53%) and integration difficulties (61%), with challenges such as legacy systems data never being prepared adequately for successful application of AI algorithms (Chen et al., 2019). All in all, these findings speak to the broader set of challenges banks grapple with when it comes to balancing tech, regs, and people when implementing AI.

8. *Summary of Key Findings*

a) AI systems perform much better than traditional systems in detecting frauds, crediting scores and processing transactions faster.
b) False positive are decreased substantially which helps in making more customers happy and reducing the operational overhead.
c) AI makes quicker and inclusive credit decisions leveraging alternate data sources
d) Understanding that most financial firms are working with legacy systems, are required to meet regulatory mandates and need an understanding for the basis of decisions made involves solutions that can be nonexistent or steeped in complexity which needs to change.
e) AI deployment is as much contingent on technical success as it is on institution readiness, regulatory compliance and human supervision.

9. Recommendations

Banks should start investing in high performance AI systems to reduce false positives, increase fraud detection and expedite faster affordable credit decisions using alternative data. To do so, institutions need to improve explainability of AI based decisions, ensure interoperability with existing legacy systems while addressing both security and privacy requirements. The objective here to facilitate the journey towards responsible, transparent AI deployment also necessitates not forsaking human supervision, cross-functional collaboration or organizational readiness in success.

10. Conclusion

This study assessed the efficiency of AI as a tool, and explored the routine operations faculties in banking industry, particularly in credit decision-making, risk management and also fraud detection. The study, which consisted of stakeholder interviews and empirical performance analysis employing both AI rule-based techniques, indicates that AI is able to outperform traditional methods with respect to efficiency, effectiveness and accuracy. For certain under-banked client segments, these technologies have shown a great deal of potential in increasing the precision of credit assessment and real-time fraud detection. Importantly, even though the promise of AI is very strong in finance, the use of this cutting-edge technology in financial organizations remains quite a bit more limited. Highlighting the necessity for banks to progress beyond mere adoption, and instead develop approaches towards governance, ethics and socially responsible/human-centered AI strategies. In addition, regulatory frameworks need to adapt to ensure that innovation does not undermine the principles of fairness, accountability and public trust. Further research should examine long-run impacts, scaling in low-resource contexts, and changing public attitudes toward AI in financial services.

References

Abdi, M., Prasad, P., Balhasan, S., Abdalgader, K., Abdelnabi, A., Hamad, A., Al Jazwe, A. B., Magomadov, I., Al-Homoud, L., Marei, N., Hassan, Z., Nagy Fathy Mohamed Mahmoud, S., & Lyakhovskaya, V. (2025). Securing the Future: Al-Driven Cybersecurity Solutions for Oil and Gas Industry. *GOTECH*, D022S004R005. https://doi.org/10.2118/224469-MS

Agrafiotis, I., Nurse, J. R. C., Goldsmith, M., Creese, S., & Upton, D. (2018). A taxonomy of cyber-harms: Defining the impacts of cyber-attacks and understanding how they propagate. *Journal of Cybersecurity*, *4*(1). https://doi.org/10.1093/cybsec/tyy006

Ahmed, S. F., Alam, Md. S. B., Hassan, M., Rozbu, M. R., Ishtiak, T., Rafa, N., Mofijur, M., Shawkat Ali, A. B. M., & Gandomi, A. H. (2023). Deep learning modelling techniques: Current progress, applications, advantages, and challenges. *Artificial Intelligence Review*, *56*(11), 13521–13617. https://doi.org/10.1007/s10462-023-10466-8

Akartuna, E. A., Johnson, S. D., & Thornton, A. (2022). Preventing the money laundering and terrorist financing risks of emerging technologies: An international policy Delphi study. *Technological Forecasting and Social Change*, *179*, 121632. https://doi.org/10.1016/j.techfore.2022.121632

Alam, S., Ayub, M. S., Arora, S., & Khan, M. A. (2023). An investigation of the imputation techniques for missing values in ordinal data enhancing clustering and classification analysis validity. *Decision Analytics Journal*, *9*, 100341. https://doi.org/10.1016/j.dajour.2023.100341

Alamsyah, A., Hafidh, A. A., & Mulya, A. D. (2025). Innovative Credit Risk Assessment: Leveraging Social Media Data for Inclusive Credit Scoring in Indonesia's Fintech Sector. *Journal of Risk and Financial Management*, *18*(2), 74. https://doi.org/10.3390/jrfm18020074

Ali, A., & Shah, M. (2024). What Hinders Adoption of Artificial Intelligence for Cybersecurity in the Banking Sector. *Information*, *15*(12), 760. https://doi.org/10.3390/info15120760

Aljunaid, S. K., Almheiri, S. J., Dawood, H., & Khan, M. A. (2025). Secure and Transparent Banking: Explainable AI-Driven Federated Learning Model for Financial Fraud Detection. *Journal of Risk and Financial Management*, *18*(4), 179. https://doi.org/10.3390/jrfm18040179

Alvi, J., Arif, I., & Nizam, K. (2024). Advancing financial resilience: A systematic review of default prediction models and future directions in credit risk management. *Heliyon*, *10*(21), e39770. https://doi.org/10.1016/j.heliyon.2024.e39770

Amershi, S., Cakmak, M., Knox, W. B., & Kulesza, T. (2014). Power to the People: The Role of Humans in Interactive Machine Learning. *AI Magazine*, *35*(4), 105–120. https://doi.org/10.1609/aimag.v35i4.2513

Asmar, M., & Tuqan, A. (2024). Integrating machine learning for sustaining cybersecurity in digital banks. *Heliyon*, *10*(17), e37571. https://doi.org/10.1016/j.heliyon.2024.e37571

Awotunde, J. B., Misra, S., Ayeni, F., Maskeliunas, R., & Damasevicius, R. (2022). Artificial Intelligence Based System for Bank Loan Fraud Prediction. In A. Abraham, P. Siarry, V. Piuri, N. Gandhi, G. Casalino, O. Castillo, & P. Hung (Eds.), *Hybrid Intelligent Systems* (Vol. 420, pp. 463–472). Springer International Publishing. https://doi.org/10.1007/978-3-030-96305-7_43

Benavides-Franco, J., Carabalí-Mosquera, J., Alonso, J. C., Taype-Huaman, I., Buenaventura, G., & Meneses, L. A. (2023). The evolution of loan volume and non-performing loans under COVID-19 innovations: The Colombian case. *Heliyon*, *9*(4), e15420. https://doi.org/10.1016/j.heliyon.2023.e15420

Berg, T., Burg, V., Gombović, A., & Puri, M. (2020). On the Rise of FinTechs: Credit Scoring Using Digital Footprints. *The Review of Financial Studies*, *33*(7), 2845–2897. https://doi.org/10.1093/rfs/hhz099

Birindelli, G., & Iannuzzi, A. P. (2025). The Systemic Importance of Cyber Risk in Banks. In V. Pacelli (Ed.), *Systemic Risk and Complex Networks in Modern Financial Systems* (pp. 301–321). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-64916-5_16

Brown, I., & Mues, C. (2012). An experimental comparison of classification algorithms for imbalanced credit scoring data sets. *Expert Systems with Applications*, *39*(3), 3446–3453. https://doi.org/10.1016/j.eswa.2011.09.033

Canhoto, A. I. (2021). Leveraging machine learning in the global fight against money laundering and terrorism financing: An affordances perspective. *Journal of Business Research*, *131*, 441–452. https://doi.org/10.1016/j.jbusres.2020.10.012

Carcillo, F., Le Borgne, Y.-A., Caelen, O., Kessaci, Y., Oblé, F., & Bontempi, G. (2021). Combining unsupervised and supervised learning in credit card fraud detection. *Information Sciences*, *557*, 317–331. https://doi.org/10.1016/j.ins.2019.05.042

Chen, T., & Guestrin, C. (2016). XGBoost: A Scalable Tree Boosting System. *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 785–794. https://doi.org/10.1145/2939672.2939785

Chen, X., Orom, H., Hay, J. L., Waters, E. A., Schofield, E., Li, Y., & Kiviniemi, M. T. (2019). Differences in Rural and Urban Health Information Access and Use. *The Journal of Rural Health*, *35*(3), 405–417. https://doi.org/10.1111/jrh.12335

Dichev, A., Zarkova, S., & Angelov, P. (2025). Machine Learning as a Tool for Assessment and Management of Fraud Risk in Banking Transactions. *Journal of Risk and Financial Management*, *18*(3), 130. https://doi.org/10.3390/jrfm18030130

Fan, J., Shar, L. K., Zhang, R., Liu, Z., Yang, W., Niyato, D., Mao, B., & Lam, K.-Y. (2025). *Deep Learning Approaches for Anti-Money Laundering on Mobile Transactions: Review, Framework, and Directions* (Version 1). arXiv. https://doi.org/10.48550/ARXIV.2503.10058

Gafsi, N. (2025). Machine Learning Approaches to Credit Risk: Comparative Evidence from Participation and Conventional Banks in the UK. *Journal of Risk and Financial Management*, *18*(7), 345. https://doi.org/10.3390/jrfm18070345

Goodell, J. W., Kumar, S., Lim, W. M., & Pattnaik, D. (2021). Artificial intelligence and machine learning in finance: Identifying foundations, themes, and research clusters from bibliometric analysis. *Journal of Behavioral and Experimental Finance*, *32*, 100577. https://doi.org/10.1016/j.jbef.2021.100577

Goyal, K., Garg, M., & Malik, S. (2025). Adoption of artificial intelligence-based credit risk assessment and fraud detection in the banking services: A hybrid approach (SEM-ANN). *Future Business Journal*, *11*(1), 44. https://doi.org/10.1186/s43093-025-00464-3

Heß, V. L., & Damásio, B. (2025). Machine learning in banking risk management: Mapping a decade of evolution. *International Journal of Information Management Data Insights*, *5*(1), 100324. https://doi.org/10.1016/j.jjimei.2025.100324

Huang, Z., Xu, Z., Wang, X., & Xu, Z. (2024). The analysis of credit governance in the digital economy development under artificial neural networks. *Heliyon*, *10*(20), e39286. https://doi.org/10.1016/j.heliyon.2024.e39286

Jagtiani, J., & Lemieux, C. (2019). The roles of alternative data and machine learning in fintech lending: Evidence from the LendingClub consumer platform. *Financial Management*, *48*(4), 1009–1029. https://doi.org/10.1111/fima.12295

Khandani, A. E., Kim, A. J., & Lo, A. W. (2010). Consumer credit-risk models via machine-learning algorithms. *Journal of Banking & Finance*, *34*(11), 2767–2787. https://doi.org/10.1016/j.jbankfin.2010.06.001

Kim, Y.-S., Kim, M. K., Fu, N., Liu, J., Wang, J., & Srebric, J. (2025). Investigating the impact of data normalization methods on predicting electricity consumption in a building using different artificial neural network models. *Sustainable Cities and Society*, *118*, 105570. https://doi.org/10.1016/j.scs.2024.105570

Krauss, C., Do, X. A., & Huck, N. (2017). Deep neural networks, gradient-boosted trees, random forests: Statistical arbitrage on the S&P 500. *European Journal of Operational Research*, *259*(2), 689–702. https://doi.org/10.1016/j.ejor.2016.10.031

Leo, M., Sharma, S., & Maddulety, K. (2019). Machine Learning in Banking Risk Management: A Literature Review. *Risks*, *7*(1), 29. https://doi.org/10.3390/risks7010029

Mennella, C., Maniscalco, U., De Pietro, G., & Esposito, M. (2024). Ethical and regulatory challenges of AI technologies in healthcare: A narrative review. *Heliyon*, *10*(4), e26297. https://doi.org/10.1016/j.heliyon.2024.e26297

Mohamed, N. (2025). Artificial intelligence and machine learning in cybersecurity: A deep dive into state-of-the-art techniques and future paradigms. *Knowledge and Information Systems*, *67*(8), 6969–7055. https://doi.org/10.1007/s10115-025-02429-y

Moura, L., Barcaui, A., & Payer, R. (2025). AI and Financial Fraud Prevention: Mapping the Trends and Challenges Through a Bibliometric Lens. *Journal of Risk and Financial Management*, *18*(6), 323. https://doi.org/10.3390/jrfm18060323

Ng, A. W., & Kwok, B. K. B. (2017). Emergence of Fintech and cybersecurity in a global financial centre. *Journal of Financial Regulation and Compliance*, *25*(4), 422–434. https://doi.org/10.1108/JFRC-01-2017-0013

Oluwabusayo Adijat Bello & Komolafe Olufemi. (2024). Artificial intelligence in fraud prevention: Exploring techniques and applications challenges and opportunities. *Computer Science & IT Research Journal*, *5*(6), 1505–1520. https://doi.org/10.51594/csitrj.v5i6.1252

Pattnaik, D., Ray, S., & Raman, R. (2024). Applications of artificial intelligence and machine learning in the financial services industry: A bibliometric review. *Heliyon*, *10*(1), e23492. https://doi.org/10.1016/j.heliyon.2023.e23492

Prabin Adhikari, Prashamsa Hamal, & Francis Baidoo Jnr. (2024). Artificial Intelligence in fraud detection: Revolutionizing financial security. *International Journal of Science and Research Archive*, *13*(1), 1457–1472. https://doi.org/10.30574/ijsra.2024.13.1.1860

Ribeiro, M. T., Singh, S., & Guestrin, C. (2016). *Model-Agnostic Interpretability of Machine Learning* (Version 1). arXiv. https://doi.org/10.48550/ARXIV.1606.05386

Ridzuan, N. N., Masri, M., Anshari, M., Fitriyani, N. L., & Syafrudin, M. (2024). AI in the Financial Sector: The Line between Innovation, Regulation and Ethical Responsibility. *Information*, *15*(8), 432. https://doi.org/10.3390/info15080432

Tambari Faith Nuka & Amos Abidemi Ogunola. (2024). AI and machine learning as tools for financial inclusion: Challenges and opportunities in credit scoring. *International Journal of Science and Research Archive*, *13*(2), 1052–1067. https://doi.org/10.30574/ijsra.2024.13.2.2258

Tayebi, M., & El Kafhali, S. (2025). A novel approach based on XGBoost classifier and Bayesian optimization for credit card fraud detection. *Cyber Security and Applications*, *3*, 100093. https://doi.org/10.1016/j.csa.2025.100093

Teodorescu, V., & Obreja Brașoveanu, L. (2025). Assessing the Validity of k-Fold Cross-Validation for Model Selection: Evidence from Bankruptcy Prediction Using Random Forest and XGBoost. *Computation*, *13*(5), 127. https://doi.org/10.3390/computation13050127

Thuy, N. T. H., Ha, N. T. V., Trung, N. N., Binh, V. T. T., Hang, N. T., & Binh, V. T. (2025). Comparing the Effectiveness of Machine Learning and Deep Learning Models in Student Credit Scoring: A Case Study in Vietnam. *Risks*, *13*(5), 99. https://doi.org/10.3390/risks13050099

Varga, S., Brynielsson, J., & Franke, U. (2021). Cyber-threat perception and risk management in the Swedish financial sector. *Computers & Security*, *105*, 102239. https://doi.org/10.1016/j.cose.2021.102239

Vicari, M., & Gaspari, M. (2021). Analysis of news sentiments using natural language processing and deep learning. *AI & SOCIETY*, *36*(3), 931–937. https://doi.org/10.1007/s00146-020-01111-x

Wang, J., Liu, G., Xu, X., & Xing, X. (2024). Credit risk prediction for small and medium enterprises utilizing adjacent enterprise data and a relational graph attention network. *Journal of Management Science and Engineering*, *9*(2), 177–192. https://doi.org/10.1016/j.jmse.2023.11.005

West, J., & Bhattacharya, M. (2016). Intelligent financial fraud detection: A comprehensive review. *Computers & Security*, *57*, 47–66. https://doi.org/10.1016/j.cose.2015.09.005

Copyrights