

Evaluating the effectiveness of AI-driven fraud detection systems in U.S. commercial banks



 **Victor Agbeve¹⁺**
Kingsford Brakye²
Edem Kwame Samlafo³
Grace Ese Odigie⁴
Sidney Abbeyquaye⁵

¹W.P Carey School of Business, Arizona State University, Arizona, USA.

¹Email: vagbeve@asu.edu

²Department of Accounting, University of South Dakota, USA.

²Email: Brakyekingsford@gmail.com

^{3,4}Thunderbird School of Global Management, Arizona State University, Arizona, USA.

³Email: esamlafo@asu.edu

⁴Email: gracyodi@gmail.com

⁵Department of Accounting, University of Ghana, Ghana.

⁵Email: betblankson@gmail.com



(+ Corresponding author)

ABSTRACT

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More advanced technologies are now required to deal with financial fraud because of the more intelligent and responsive systems available in the U.S. banking sector. This research focuses on the impact of AI on fraud detection systems within commercial banks in the U.S. through a systematic literature review of articles. Implementing and adopting various AI technologies, such as neural networks, support vector machines, decision trees, and graph neural networks, have demonstrated remarkable achievements in identifying complex fraud, monitoring in real-time, and reducing false positive rates. Results show that the integration of AI technologies with bank operational processes has improved detection accuracy and operational efficiency, enhanced customer loyalty, and met regulatory standards. Furthermore, the study reveals gaps such as a lack of model transparency, ethical implications, and information bias. The application of explainable AI (XAI) and hybrid solutions promises to address these issues. Incorporating these technologies facilitates adaptation to changes in internet-based financial transactions. It also helps eliminate gaps associated with current AI systems that are not fully controllable, due to the nature of information related to fraud. These systems reduce previously identified gaps in modern banking fraud prevention, complementing AI-based technologies. Additionally, the results emphasize the importance of secure infrastructures based on advanced AI fraud detection techniques. The findings contribute to broadening conventional perceptions of banking, allowing for sensible adaptation to the rapid growth and shifts in the financial world and digital economy.

Contribution/ Originality: This study contributes to the existing literature by evaluating the impact of AI-driven fraud detection systems in U.S. commercial banks. It combines various AI technologies, including neural networks and decision trees, to assess their effectiveness in real-time fraud detection. The study is one of the few that integrates Explainable AI (XAI) to address transparency and model fairness in banking fraud detection systems.

1. INTRODUCTION

The banking sector is utilizing AI and automation technologies to modernize crime prevention and fraud detection systems, as they seek to improve customer service and effectively balance costs (Venu, 2025). The wider digitalization of the banking sector has increased cybercrime and identity theft (Venu, 2025). Agile cybercriminals

employing increasingly sophisticated techniques have outpaced traditional fraud detection systems based on rules (Venu, 2025). AI-based fraud detection systems are increasingly deployed in banking, insurance, and healthcare due to their effectiveness and adaptability (Adhikari, Hamal, & Jnr, 2024). Adopting AI technologies to enhance compliance with regulatory requirements regarding fraud detection and risk management is becoming the norm among American banks (Joshi, 2021). These include machine learning, natural language processing, and even predictive analytics, which are integrated to permit timely and accurate analysis by the banks (Kapate, Sikwal, & Bhambhani, 2025). Using a combination of machine learning, deep learning, NLP, and AI, fraud detection is becoming easier since the algorithms of these systems can recognize patterns and anomalies that suggest fraudulent activities (Ellahi et al., 2024). Tracking and analyzing transactions and suspicious activities in real time enable banks to react quickly to most threats (Nagendra & Ramesh, 2025). The accuracy, efficiency, and scalability of fraud detection are improved with AI-based systems (Boateng, Amoako, Ajay, & Adukpo, 2025). AI technology is revolutionizing fraud detection with machine learning algorithms such as Support Vector Machines (SVM) and Decision Trees, enabling banks to instantly identify fraudulent behavior, money laundering, and other suspicious activities (Islam & Rahman, 2025; Joshi, 2021). Within the banking sector, AI helps process unstructured data, decreasing operational expenditures while improving decision-making speed and safety (Kulkarni, 2024). AI systems assist Nagendra and Ramesh (2025) in recognizing patterns and anomalies within large datasets that signal potential fraudulent activity. Besides, fraud is detected faster, and AI increases the efficiency of customer engagement and banking operations (Shivani, Kumar, & Chandra, 2025). AI-based fraud detection systems still face adoption hurdles (Yaseen & Al-Amarneh, 2025).

For instance, ghost no-show bias and lack of clear explainability of decisions can be major stumbling blocks, especially in the banking sector that focuses on compliance (Yaseen & Al-Amarneh, 2025). To reduce trust erosion, as well as strengthen the financial ecosystem, XAI needs to be implemented throughout the framework and risk assessment processes (Černevičienė & Kabašinskas, 2024). Defending complex algorithm-based model outcomes is just as important as checking for bias and model fairness (Černevičienė & Kabašinskas, 2024). The explainability and performance of fraud detection systems can be enhanced by integrating fuzzy logic into Deep Symbolic Regression (DSR (Gerdes & Acar, 2024). Commercial banks in the U.S. are at risk of high-level sophisticated fraud as they process trillions of transactions in a year, thus needing tech-based solutions (Shivani et al., 2025; Venu, 2025). Every machine has its errors; in the case of AI, financial fraud patterns are detected with incredible accuracy and flexibility, allowing entire systems to adapt and identify new abnormal behaviors (Boateng et al., 2025; Kapate et al., 2025). This research underscores the fundamental necessity of adopting AI solutions to enhance the integrity of financial data.

1.1. Overview of U.S. Banking Fraud Detection Systems: Recent Advances Due to Technology and AI Implementation

The deployment of AI technologies has transformed fraud detection systems in banking in the US, offering advanced capabilities to detect potential risks and threats (Hindolia, 2025; Islam & Rahman, 2025; Venu, 2025). AI tools such as ML, DL, and NLP have become central to improving these systems' precision, effectiveness, and expansion (Boateng et al., 2025; Ellahi et al., 2024). The advanced and faster systems have enabled monitoring and alerting systems to function in real-time, incorporated automation, improved customer safeguarding, and ensured regulatory compliance using advanced analytics and data processing (Ahmadi, 2025; Dalsaniya, Patel, & Swaminarayan, 2025; Venu, 2025).

1.1.1. Machine Learning Methods for Identifying Deceitful Behaviour in Services

The large volume of data to be handled and intricate patterns to be recognized have made AI a worthwhile investment in fraud detection. To detect fraud, machine learning methodologies such as logistic regression, decision trees, and neural networks are employed for the instantaneous detection of fraud, money laundering, and other associated criminal offenses (Boateng et al., 2025; Joshi, 2021). AI-powered systems have a greater ability to adjust

to new fraud methods than older, more rigid systems that rely on a fixed set of rules (Adhikari et al., 2024; Thakkar, 2024). In addition, Shubham (2025) and Kartheek (2024) highlight that risk assessment models driven by AI have further improved the detection and prevention of fraud tailored to predictive intelligence across financial institutions. Using unsupervised learning techniques that enable systems to detect threat patterns with no labelled data makes these systems robust and flexible to evolving risks (Kumar & Kiran, 2025). As an illustration, encoder-decoder graph neural networks use connections between entities like merchants and customers to identify credit card fraud (Cherif, Ammar, Kalkatawi, Alshehri, & Imine, 2024). These networks enhance accuracy through relevant feature selection, which improves the detection of fraudulent transactions as opposed to non-fraudulent ones (Cherif et al., 2024). To deepen model interpretability, XAI techniques, notably SHAP (SHapley Additive exPlanations), offer the rationale behind their outputs, thus enhancing the model's ability to explain its processes (Ahmadi, 2025; Gangavarapu, Daiya, Puri, & Narlawar, 2024). Social or ethical considerations regarding the use of AI systems to detect fraud center on transparency (Černevičienė & Kabašinskas, 2024).

1.1.2. The Opportunities and Challenges of AI Technologies and Their Impact on Fraud Detection

Most AI technologies can enhance fraud detection; nevertheless, there are limitations to their use. Noisy labels within the training data are one such problem, as they can limit the creation of efficient models. Tackling this problem would require applying disentangled distribution learning coupled with consistency regularization to alleviate the impact of noisy labels. Machine learning model vulnerabilities to hostile interference are another challenge where anti-social elements manipulate the system by injecting malicious data (Paladini, Monti, Polino, Carminati, & Zanero, 2023). In this case, research has been conducted to develop methods for diagnosing and handling such interference attempts, thereby maintaining the integrity of fraud detection systems (Paladini et al., 2023). AI in fraud detection presents numerous possibilities. Automation driven by artificial intelligence can make repetitive tasks like transaction monitoring and alert creation more efficient, allowing human analysts to devote attention to more convoluted cases (Dalsaniya et al., 2025). This enhances decision-making speed and minimizes operational costs (Kulkarni, 2024). The application of AI in conjunction with RPA intensifies the EFPDA, increasing the responsiveness of financial institutions to new threats (Dalsaniya et al., 2025). AI improves bank security by offering advanced protection systems against complex financial fraud and cyberattacks (Kumar & Kiran, 2025; Olowu et al., 2024).

1.1.3. Impact on Bank Security and Trust of Customers

The implementation of AI in fraud detection systems has a direct impact on banking security and customer trust. AI makes fraud detection more accurate and scalable, thus improving the safeguarding of financial transactions and the protection of customers from financial crimes (Johora, Hasan, Farabi, Akter, & Al Mahmud, 2024; Venu, 2025). As financial security measures improve, customers gain more trust in digital banking services, increasing their adoption and usage (Venu, 2025). Moreover, trust is reinforced through the use of explainable AI (XAI), which elucidates the rationale behind AI decisions, thus assuring customers that fraud detection measures are unbiased and discrimination-free (Černevičienė & Kabašinskas, 2024). However, the ethical considerations concerning AI technologies, such as privacy, fairness, and adherence to regulations, must be addressed (Adhikari & Jnr, 2025; Ridzuan, Othman, Juri, Ghani, & Haron, 2024). These institutions also require building frameworks around responsible AI actions to ensure a sound and resilient financial system (Ridzuan et al., 2024).

1.1.4. Future Outlook

With the advancements of technology, artificial intelligence will be able to uncover fraud and cyber threats in more advanced ways. Blockchain technology, the Internet of Things (IoT), and proactive cyber threat detection will incorporate AI, resulting in more sophisticated machine learning systems (Cao, 2022; Ellahi et al., 2024). The carbon

footprint of AI also poses an unresolved problem. In turn, proportional non-compliance of the banking sector will necessitate an eco-respectful, non-compliant framework (Tkachenko, 2024).

2. METHODOLOGY

This study aimed to analyze the effects of AI-driven fraud detection systems on U.S. commercial banks regarding technological advancements and their implementation outcomes. It followed a qualitative, literature-based research design that was systematically reviewed and critically analyzed. A content analysis methodology from prior scholarly work was also used. Priority was given to publications concentrating on the application of AI in banking, financial fraud detection, performance evaluation of models, and implementation problems. Several important sources included Google Scholar, ResearchGate, ScienceDirect, and the websites of high-impact open-access journals. Also, all studies had to meet three guidelines to be accepted: (1) focus on fraud detection through AI or machine learning, (2) pertain to the U.S. banking context, and (3) present qualitative or quantitative insights. Classification was made concerning the AI strategies and their application in fraud detection in banks; documented benefits and outcomes post-implementation, and key hurdles about integrating AI into banking operations. The culmination of the research was captured in a table highlighting patterns regarding the reported cases, the cited works, and the AI technologies in question. In this case, the approach synthesized the works of different scholars and ensured a grounded overview in authentic peer-reviewed literature, devoid of invented or speculative data.

3. RESULTS

Insights into the literature reviewed revealed that significant developments and outcomes have resulted from implementing fraud detection systems using AI technology in commercial banks in the United States. The results are displayed in three tables formulated to showcase these technologies' efficacy, advantages, and difficulties.

Table 1. AI Techniques and Their Applications in Fraud Detection.

AI Technique	Key Application Area	Supporting Study
Support Vector Machines (SVM)	Real-time detection of money laundering and suspicious transactions	Joshi (2021)
Decision Trees	Identifying and flagging fraudulent transactions	Joshi (2021) and Islam and Rahman (2025)
Graph Neural Networks (GNN)	Credit card fraud detection via merchant–customer relationship mapping	Cherif et al. (2024)
Logistic Regression	Fraud classification using historical transaction patterns	Boateng et al. (2025)
Neural Networks	Real-time anomaly detection in transactional datasets	Ellahi et al. (2024) and Boateng et al. (2025)
Deep Symbolic Regression + Fuzzy Logic	Enhancing model explainability and decision accuracy	Gerdes and Acar (2024)

Table 2. Documented benefits of AI implementation in U.S. Banking.

Benefit achieved	Description	Source
Real-time monitoring and alerts	AI models enable instant detection of suspicious activity across millions of transactions.	Islam and Rahman (2025) and Nagendra and Ramesh (2025)
Improved fraud detection accuracy	Use of deep learning and unsupervised learning increases precision in identifying threats.	Boateng et al. (2025) and Kumar and Kiran (2025)
Operational cost reduction	Automated systems reduce the need for manual investigation.	Kulkarni (2024) and Dalsaniya et al. (2025)
Enhanced customer protection	Fast detection and prevention boost client trust in digital banking.	(Venu, 2025); and Johora et al. (2024)
Regulatory compliance support	AI supports auditing and real-time reporting to meet financial regulations.	Dalsaniya et al. (2025) and Ahmadi (2025)
Pattern recognition from big data	AI identifies complex fraud schemes by detecting hidden patterns in transactional datasets.	Ellahi et al. (2024) and Kapate et al. (2025)

Table 3. Challenges identified in AI-driven fraud detection.

Challenge	Description	Suggested mitigation	Reference
Noisy labels in training data	Incorrect labeling affects model performance	Disentangled distribution learning, consistency regularization	
Adversarial attacks	Attackers manipulate data inputs to mislead AI models.	Defensive model training and adversarial detection tools	Paladini et al. (2023)
Algorithmic bias and opacity	Lack of explainability hinders model acceptance	Use of Explainable AI (e.g., SHAP)	Černevičienė and Kabašinskas (2024) and Ahmadi (2025)
Regulatory and ethical concerns	Risks of discrimination and lack of transparency in automated decisions	Responsible AI practices and fairness-aware training	Adhikari and Jnr (2025) and Ridzuan et al. (2024)
Integration with legacy systems	Technical and operational barriers in adopting AI into older banking systems	Use of Robotic Process Automation (RPA) + modular AI	Dalsaniya et al. (2025) and Kulkarni (2024)

4. DISCUSSION

The findings in this study contribute significantly to understanding the impact of AI technologies on fraud detection in commercial banking in the United States. From the compiled literature, three key tables identify and summarize the important patterns emerging from applying particular AI methods, the quantifiable improvements made, and the operational difficulties faced.

The application of AI for sophisticated fraud detection is more or less uniform, as illustrated in Table 1. SVM and decision trees are quite useful in real-time detection of anomalies and classifying transactions into fraudulent and non-fraudulent categories (Islam & Rahman, 2025; Joshi, 2021). Larger datasets flooded with intricate and complex information are best processed by neural networks or logistic regression models because they detect fraud attendant to the dataset's intricacies (Boateng et al., 2025; Ellahi et al., 2024). More importantly, GNNs or Graph Neural Networks are a recent development that allows examination of relational data, such as merchants' and customers' interactions, for fraud ring detection (Cherif et al., 2024). The proliferation of sophisticated deep learning approaches and advanced graph-based techniques indicates a broad industry trend toward adaptive and scalable fraud detection systems.

Furthermore, incorporating XAI and hybrid models like Deep Symbolic Regression with fuzzy logic responds to the need for transparency and explainability in global model decisions (Ahmadi, 2025; Gerdes & Acar, 2024). This is pivotal for compliance and stakeholder trust. Results in Table 2 corroborate that the operational advantages of AI integration are considerable. The effectiveness and precision of fraud detection in systems with a high volume of transactions are enhanced by real-time monitoring and automated alert technologies (Nagendra & Ramesh, 2025). These systems reduce the burden on human analysts and decrease the rate of false positives, which have plagued traditional fraud detection systems (Boateng et al., 2025; Kumar & Kiran, 2025). Reduction in operational expenses is also notable due to AI and automation's impact on manual review and investigation workflows (Dalsaniya et al., 2025; Kulkarni, 2024).

Additionally, AI implementation improves regulatory compliance by allowing precise tracking, reporting, and audit trails of flagged financial activities (Ahmadi, 2025). Venu (2025) and Johora et al. (2024) highlight that, from a customer-driven standpoint, better detection translates into improved safety and trust, which drives the adoption of digital banking services. While these outcomes are positive, Table 3 shows some issues that still restrict AI technologies' effective and widespread use in fraud detection. One of the main issues is noisy labels in training datasets, which lead to poor performance and increased error rates in classification. This applies to the banking sector, where labeled datasets for fraud are often sparse and imprecise due to human biases. The integration of RPA and AI is considered an emerging technology that can streamline and accelerate the processes associated with an organization's integration system, allowing for faster detection of fraud within frameworks (Dalsaniya et al., 2025; Kulkarni, 2024).

5. CONCLUSION

Implementing Artificial Intelligence (AI) technologies has mitigated operational risks for U.S. commercial banks by automating processes within fraud detection systems. The application of financial AI models, including but not limited to neural networks, decision trees, support vector machines, and graph-based algorithms, has automated the identification and processing of fraudulent activities. This study examines AI's application in real-time monitoring of fraud and predictive analytics in advanced customer protection, ensuring adherence to legal mandates, and providing optimized guidance for regulators. Trust in digital banking has grown as operational efficiency improves. The review identifies the necessity of AI integration into banking legacy systems, creating low-adaptability AI, data accuracy challenges, seamless integration, and ongoing refinement. The increasing application of explainable AI (XAI), hybrid learning models, and responsible AI frameworks bolsters accountability for transparency, fairness, and sustainable progress. AI-based systems have transformed risk management and security frameworks concerning financial transactions.

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