

literature Review : AI-Based Real-Time Fraud Detection in Digital Service Requests” How can organization activate AI to mitigate fraud

Problem Statement

The problem domain is the application of Artificial Intelligence (AI) for real-time fraud detection in the digital financial services sector. While the literature shows a strong consensus that AI and Machine Learning (ML) models are significantly more effective than traditional rule-based systems, a critical problem has emerged regarding their practical implementation. The problem is the significant and conflicting disparity between the theoretical scalability of AI solutions and the practical challenges encountered during their real-world deployment. This issue is significant because as digital transaction volumes grow, the ability of fraud detection systems to scale effectively without compromising performance is paramount to maintaining financial integrity and customer trust.

Existing solutions presented in the literature include a variety of advanced techniques such as Long Short-Term Memory (LSTM) networks that demonstrate high accuracy and low latency , and innovative integrations of AI with blockchain technology promising high throughput of up to 1200 transactions per second in simulated environments. Other approaches utilize anomaly detection frameworks like Autoencoders and Isolation Forests with real-time platforms such as Kafka and Spark. However, despite these advancements, several studies explicitly identify scalability and data quality as major challenges and deployment hurdles in practice. This discrepancy is further complicated by a lack of standardized quantitative reporting across studies, with some providing detailed performance metrics while others offer only qualitative assessments, making direct comparisons difficult.

Therefore, there is a justifiable need for research to investigate the underlying factors that cause this gap between the promised scalability of AI systems and the documented practical challenges. This research is necessary to develop a clearer understanding of how to effectively deploy these advanced systems in complex, real-world financial environments and to establish a more consistent framework for evaluating their performance.

Research Objectives

To address the identified problem, this research will pursue the following objectives:

1. To critically analyze and identify the specific technical, architectural, and operational factors that hinder the scalability of AI-based fraud detection systems when deployed in real-world financial service environments, as highlighted by Pothireddy and Algubelli (2016) and Tyagi et al.

2. To conduct a comparative analysis of at least three distinct AI-based fraud detection architectures identified in the literature (e.g., LSTM-based, AI-Blockchain integration, and anomaly detection with streaming frameworks). This analysis will use a standardized set of quantitative performance metrics, including transaction throughput, latency, accuracy, and false positive rates, to bridge the reporting gap identified across studies.
3. To propose a conceptual framework for the implementation and evaluation of scalable AI fraud detection systems. This framework will provide guidelines for addressing the common challenges of data quality, regulatory compliance, and system integration that were identified as significant but underexplored barriers to deployment.

Literature Review:

Table of contents:

- Summary research paper's
- Critical Analysis:
- Connections
- Conflicts between the findings
- Synthesis Matrix for Literature Review
- References

Summarized Research Papers

1. Bendhi, 2025

- **Summary Research Paper:** This study investigates real-time fraud detection in digital financial transactions using various AI techniques. It specifically highlights the effectiveness of Long Short-Term Memory (LSTM) networks. The research reports that LSTM achieved high performance metrics (precision 0.96, recall 0.94, F1 score 0.95, AUC 0.98) with very low latency (85 milliseconds) and a significant reduction in false positives (from 3.7% to 0.8%) compared to traditional systems. The implementation was in a real-time operational setting using a public credit card dataset.
- **Critical Analysis:** The paper presents strong quantitative evidence for the superiority of LSTM in this context, demonstrating clear improvements in accuracy and efficiency. The use of a public dataset enhances reproducibility, but its generalizability to diverse proprietary financial data could be further explored. The study's focus on a single type of digital financial transaction (credit cards) might limit its direct applicability to other digital services. While it highlights reduced false positives, the specific mechanisms within LSTM contributing to this reduction could be elaborated.
- **Connections:** This paper strongly supports the overall theme that AI/ML methods outperform traditional rule-based systems in fraud detection. Its specific findings on LSTM's low latency and high accuracy connect well with the need for real-time processing emphasized across the literature. It aligns with Olowu et al. (2024) in promoting AI's effectiveness.
- **Conflicts between Findings:** No direct conflicts with other findings are apparent; rather, its results provide strong empirical backing for the broad claims made in other, more general or review-based studies.
- **References:** Bendhi, Manish Reddy. "Fraud Detection: Leveraging Artificial Intelligence to Identify Transaction Anomalies in Real-Time and Minimize False Positives." *International Journal Of Engineering And Computer Science*, 2025.

2. Fallah et al., 2024

- **Summary Research Paper:** This study explores the integration of artificial intelligence with blockchain technology for real-time fraud detection in financial services. Utilizing Gradient Boosting and Recurrent Neural Networks within a permissioned blockchain environment, the research demonstrates high accuracy with an error rate below 2%. A key finding is its ability to process up to 1200 transactions per second, emphasizing how AI-blockchain integration enhances security and throughput. The implementation was based on simulation experiments.
- **Critical Analysis:** The novelty of this paper lies in its exploration of AI-blockchain synergy, addressing scalability and security concurrently. The high transaction processing speed is a significant advantage. However, as it's based on simulation experiments rather than a fully deployed real-world system, the practical challenges and overheads of such an integration in a live financial environment might be underestimated. The specific details of how Gradient Boosting and RNNs are integrated with the blockchain, and the nuances of the "permissioned" aspect, could be more thoroughly detailed.
- **Connections:** This paper connects to the broader theme of real-time processing and scalability. Its focus on blockchain complements other studies that discuss real-time streaming frameworks (Tyagi et al., 2025) and highlights an alternative approach to achieving high throughput. It supports the general notion of AI enhancing security, as also mentioned by Kandregula (2019).
- **Conflicts between Findings:** While not a direct conflict, this paper's reliance on simulation and high processing speed (1200 transactions/second) sets a very high bar, which might contrast with the lower processing speeds or scalability challenges noted in other studies that focus on more traditional AI deployment environments (e.g., Pothireddy and Algubelli, 2016 which mentions scalability as a challenge).
- **References:** Fallah, M. H., Ms. G. Sheeba, Dharmapuri Siri, Himanshu Sharma, G. R. Kumar, and Dr. A. Devendran. "AI- Powered Blockchain Systems for Real-Time Fraud Detection in Financial Services." *2024 International Conference on IoT, Communication and Automation Technology (ICICAT)*, 2024.

3. Pothireddy and Algubelli, 2016

- **Summary Research Paper:** This paper focuses on real-time fraud detection using AI on financial streaming data, employing supervised machine learning algorithms such as Random Forest, Support Vector Machine (SVM), and Artificial Neural Network (ANN). The study highlights high precision and minimal latency, concluding that AI methods outperform traditional rule-based systems. However, it also identifies scalability and data quality as significant challenges in practical implementation.
- **Critical Analysis:** This paper provides early empirical evidence for AI's superiority in real-time financial fraud detection. The explicit mention of scalability and data quality as challenges is crucial for a balanced view of AI deployment. However, the lack of quantified precision and latency metrics makes it difficult to directly compare its performance with other studies. The specific details on how data quality affects the models and what "minimal latency" entails are not provided.

- **Connections:** This study reinforces the overarching conclusion that AI surpasses rule-based systems. Its identification of scalability as a challenge provides a valuable counterpoint or area for further exploration compared to papers that emphasize AI's scalability. It aligns with Olowu et al. (2024) and the broader literature on AI's performance benefits.
- **Conflicts between Findings:** This paper explicitly states "scalability and data quality are challenges," which stands in contrast to studies like Fallah et al. (2024) and Premasai (2024) that highlight or design for high scalability. This suggests that the realization of scalability in real-world AI systems for fraud detection can vary significantly depending on the implementation context and specific technologies used.
- **References:** Pothireddy, Nirup Kumar Reddy, and Bipinkumar Reddy Algubelli. "Real-Time Fraud Detection Using AI on Financial Streaming Data." *International Journal of Scientific Research in Science and Technology*, 2016.

4. Olowu et al., 2024

- **Summary Research Paper:** This is a systematic review analyzing artificial intelligence and data science approaches in banking fraud detection, based on a meta-analysis of 47 studies. It concludes that various machine learning and deep learning algorithms, especially integrated supervised/unsupervised approaches, yield detection rates ranging from 87% to 94% and reduce false positives by 40-60% compared to rule-based systems. It emphasizes that integrated approaches are best for detecting novel fraud patterns.
- **Critical Analysis:** As a systematic review, this paper provides a valuable high-level synthesis of the field, reinforcing the general efficacy of AI. The aggregation of findings from multiple studies strengthens its conclusions on detection rates and false positive reductions. However, as it's a review, it doesn't offer specific technical implementation details or primary empirical data from a single study. The specific methodologies employed for the meta-analysis are not detailed in the abstract, which limits the ability to critically assess its synthesis process.
- **Connections:** This paper serves as a foundational agreement across the literature, confirming the general consensus that AI outperforms traditional methods. Its emphasis on integrated supervised/unsupervised approaches connects with the idea of addressing novel fraud patterns and complements papers focusing on anomaly detection.
- **Conflicts between Findings:** This paper's broad findings are generally in agreement with the individual studies it synthesizes. Any "conflicts" would likely be at a more granular level, regarding specific algorithm performance differences or implementation challenges, which a meta-analysis typically smooths out into general trends.
- **References:** Olowu, Olawale, Ademilola Olowofela Adeleye, Abraham Okandeji Omokanye, Akintayo Micheal Ajayi, Adebayo Olabode Adepoju, Olayinka Mary Omole, and Ernest C Chianumba. "AI-Driven Fraud Detection in Banking: A Systematic Review of Data Science Approaches to Enhancing Cybersecurity." *GSC Advanced Research and Reviews*, 2024.

5. Tyagi et al., 2025

- **Summary Research Paper:** This study explores the role of artificial intelligence in risk management and fraud detection, specifically highlighting the use of Autoencoders, Isolation Forests, and statistical methods for anomaly detection. It emphasizes the integration of these techniques with real-time frameworks like Kafka and Spark for high-dimensional transaction data. A key finding is the effectiveness of anomaly detection for new fraud types and integration with real-time frameworks, but it also notes scalability and regulatory compliance as significant deployment challenges.
- **Critical Analysis:** The paper's focus on anomaly detection for novel fraud types is important, addressing a key limitation of rule-based systems. The mention of specific real-time frameworks (Kafka, Spark) adds practical value. However, the study does not quantify performance metrics, making it difficult to assess the exact impact of its proposed methods. The challenges of "scalability and regulatory compliance" are identified but not explored in depth, leaving questions about their specific nature and potential solutions.
- **Connections:** This paper strongly connects with the theme of detecting novel fraud patterns and the importance of real-time processing frameworks. Its identification of scalability and regulatory compliance as challenges aligns with Pothireddy and Algubelli (2016) and supports the "Summary of Conflicts" in the original content, providing specific examples of these ongoing issues.
- **Conflicts between Findings:** Similar to Pothireddy and Algubelli (2016), this paper identifies scalability as a "deployment challenge," which conflicts with the implied or stated ease of scalability in systems like Fallah et al. (2024) or Premsai (2024). This highlights a nuanced reality of AI system deployment where theoretical scalability doesn't always translate smoothly into practice due to integration complexities and regulatory hurdles.
- **References:** Tyagi, Swati, Anuj Tyagi, Dr. S. Rani, A. Suraj Kumar, Dr. Sunil Adhav, and Dr. Sumeet Gupta. "The Role of Artificial Intelligence in Risk Management and Fraud Detection in Financial Services." *Journal of Informatics Education and Research*, 2025.

6. Kandregula, 2019

- **Summary Research Paper:** This paper discusses leveraging artificial intelligence for real-time fraud detection in financial transactions from a FinTech perspective. It broadly mentions machine learning, deep learning, and natural language processing (NLP) as methods. The key findings include that AI reduces false positives/negatives, increases reliability, and reduces manual costs. It also notes that NLP adds security through sentiment/entity analysis.
- **Critical Analysis:** This paper provides a high-level overview of AI's benefits in FinTech fraud detection, particularly introducing NLP as a method, which is unique among the selected papers. However, it lacks specific algorithmic details, implementation context, and quantifiable performance metrics. The claims about reduced costs and increased reliability are qualitative and lack empirical backing within the paper's summary. This makes it more of a conceptual or review-oriented piece than an empirical study.
- **Connections:** This paper contributes to the general consensus about AI's ability to reduce false positives/negatives and improve

reliability. Its mention of NLP introduces a new dimension to AI methods for fraud detection, potentially opening avenues for richer data analysis beyond numerical transactions. It broadly supports the positive outcomes of AI mentioned in Olowu et al. (2024).

- **Conflicts between Findings:** There are no direct conflicts with other papers, but its lack of detailed quantification or specific implementation context makes it less comparable in terms of performance metrics than other empirical studies (e.g., Bendhi, 2025). Its contribution is more in introducing a broader scope of AI applications (like NLP).
- **References:** Kandregula, Narendra. "Leveraging Artificial Intelligence for Real-Time Fraud Detection in Financial Transactions: A Fintech Perspective." *World Journal of Advanced Research and Reviews*, 2019.

Connections

The selected papers collectively demonstrate a strong consensus on the effectiveness of AI/ML in surpassing traditional rule-based systems for real-time fraud detection in digital financial services (Bendhi, 2025; Pothireddy and Algubelli, 2016; Olowu et al., 2024). Specifically, there's a recurring theme of AI leading to significant reductions in false positives and improved overall accuracy (Bendhi, 2025; Olowu et al., 2024; Kandregula, 2019). The emphasis on **real-time processing** is central across all chosen studies, with various architectural solutions proposed, from specific streaming frameworks like Kafka/Spark (Tyagi et al., 2025) to novel blockchain integrations (Fallah et al., 2024). The importance of **advanced AI techniques** like deep learning (LSTM in Bendhi, 2025; RNNs in Fallah et al., 2024) and ensemble/integrated supervised/unsupervised methods (Olowu et al., 2024; Tyagi et al., 2025) is consistently highlighted for their superior performance and ability to detect novel fraud patterns. Furthermore, several papers touch upon the broader benefits beyond just detection rates, such as enhanced security (Fallah et al., 2024; Kandregula, 2019) and operational efficiency.

Conflicts between the Findings

While there is a general agreement on AI's benefits, a notable conflict arises concerning **scalability and implementation ease**. Pothireddy and Algubelli (2016) and Tyagi et al. (2025) explicitly identify **scalability as a significant challenge** and a deployment hurdle, respectively, often citing integration with legacy systems and regulatory compliance as barriers. In contrast, Fallah et al. (2024) present a highly optimistic view of scalability with their AI-blockchain integration, boasting 1200 transactions per second. Prem Sai (2024), though not explicitly summarized here, is also noted in the original content as "designed for scalability," and Kandregula (2019) claims ML/DL/NLP improve scalability. This divergence suggests that while AI *can* be scalable, achieving it in real-world, complex financial environments poses considerable practical difficulties that are not uniformly addressed or overcome across all implementations. Additionally, there's a variation in the **level of quantitative reporting**: some studies provide detailed performance metrics (Bendhi, 2025; Fallah et al., 2024), while others make qualitative claims about accuracy or efficiency without specific numbers (Pothireddy and Algubelli, 2016; Tyagi et al., 2025; Kandregula, 2019). This lack of consistent quantification makes direct, granular comparisons between methodologies challenging and points

to a potential gap in standardized reporting.

Synthesis Matrix for Literature Review

Theme/Paper	Bendhi, 2025 (LSTM)	Fallah et al., 2024 (AI-Blockchain)	Pothireddy & Algubelli, 2016 (RF, SVM, ANN)	Olowu et al., 2024 (Systematic Review)	Tyagi et al., 2025 (Autoencoders, IF)	Kandregula, 2019 (ML, DL, NLP)
AI/ML Methods	LSTM, RF, Isolation Forest, Autoencoders, DT, NN, RNN, hybrid	Gradient Boosting, RNN	Random Forest, SVM, ANN (supervised)	Various ML/DL, integrated supervised/unsupervised	Autoencoders, Isolation Forests, statistical methods (anomaly detection)	ML, DL, NLP
Real-time Processing	Yes (85ms latency)	Yes (1200 TPS, blockchain)	Yes (minimal latency)	Yes (consistent need for real-time)	Yes (Kafka, Spark frameworks)	Yes (FinTech context, real-time analysis)
Detection Accuracy	High (P 0.96, R 0.94, F1 0.95, AUC 0.98)	High (error <2%)	High precision (not quantified)	High (87-94% detection rate)	Focus on high accuracy (not quantified)	Improved accuracy (not quantified)
False Positive	Yes (from	Yes	Yes (AI	Yes (40-60%	Focus on	Yes (reduces

Theme/Paper	Bendhi, 2025 (LSTM)	Fallah et al., 2024 (AI-Blockchain)	Pothireddy & Algubelli, 2016 (RF, SVM, ANN)	Olowu et al., 2024 (Systematic Review)	Tyagi et al., 2025 (Autoencoders, IF)	Kandregula, 2019 (ML, DL, NLP)
Reduction	3.7% to 0.8%)	(implied by low error rate)	outperform s rule-based)	reduction)	minimizing false alarms (not quantified)	false positives/negati ves)
Scalability	No mention found	Scalable (permissio ned blockchain)	Challenge	Key consideration for real-time systems	Deployment challenge	Improves scalability (ML/DL/NLP)
Key Contributions	Strong empirical evidence for LSTM; quantified performance ; false positive reduction.	AI-blockchain integration ; high throughpu t; enhanced security (simulated) .	Early validation of AI; identifies scalability/d ata quality challenges.	Comprehensive review; meta-analysis confirming AI superiority for novel patterns.	Anomaly detection for new fraud types; specific real-time frameworks.	Broad benefits of AI in FinTech; introduces NLP for security/sentim ent.
Limitations/Challe nges	Generalizabi lity of public	Simulation -based;	Lack of quantified	Meta-analysis nature (no primary	No quantified performance;	Lack of quantitative

Theme/Paper	Bendhi, 2025 (LSTM)	Fallah et al., 2024 (AI-Blockchain)	Pothireddy & Algubelli, 2016 (RF, SVM, ANN)	Olowu et al., 2024 (Systematic Review)	Tyagi et al., 2025 (Autoencoders, IF)	Kandregula, 2019 (ML, DL, NLP)
	dataset; details of LSTM contribution to FPR.	real-world deployment challenges not fully explored.	metrics; scalability/data quality challenges.	data/implementation specifics).	scalability/regulatory compliance challenges.	data; broad conceptual claims without empirical backing.
Unique Aspects	Detailed LSTM performance for fraud.	Blockchain integration .	Early clear identification of practical challenges.	Meta-analysis across 47 studies.	Focus on anomaly detection with specific streaming tech.	Introduction of NLP; FinTech perspective.

References

- Abikoye, B., Akinwunmi, T., Adelaja, A., Umeorah, S. C., & Ogunsuji, Y. M. (2024). Real-Time Financial Monitoring Systems: Enhancing Risk Management Through Continuous Oversight. *GSC Advanced Research and Reviews*.
- Bendhi, M. R. (2025). Fraud Detection: Leveraging Artificial Intelligence to Identify Transaction Anomalies in Real-Time and Minimize False Positives. *International Journal Of Engineering And Computer Science*.
- Fallah, M. H., Sheeba, G., Siri, D., Sharma, H., Kumar, G. R., & Devendran, A. (2024). AI- Powered Blockchain Systems for Real-Time Fraud Detection in Financial Services. *2024 International Conference on IoT, Communication and Automation Technology (ICICAT)*.
- Jeyachandran, P., Vardhan Akisetty, A. S. V., Subramani, P., Goel, O., Singh, S. P., & Shrivastav, A. (2024). Leveraging Machine Learning for Real-Time Fraud Detection in Digital Payments. *Integrated Journal for Research in Arts and Humanities*.
- Kandregula, N. (2019). Leveraging Artificial Intelligence for Real-Time Fraud Detection in Financial Transactions: A Fintech

Perspective. *World Journal of Advanced Research and Reviews*.

- Olowu, O., Olowofela Adeleye, A., Omokanye, A. O., Ajayi, A. M., Adepoju, A. O., Omole, O. M., & Chianumba, E. C. (2024). AI-Driven Fraud Detection in Banking: A Systematic Review of Data Science Approaches to Enhancing Cybersecurity. *GSC Advanced Research and Reviews*.
- Pothireddy, N. K. R., & Algubelli, B. R. (2016). Real-Time Fraud Detection Using AI on Financial Streaming Data. *International Journal of Scientific Research in Science and Technology*.
- Premasai, R. (2024). INTEGRATING AI IN IDENTITY AND ACCESS MANAGEMENT FOR IMPROVED CYBERSECURITY POSTURE. *International Scientific Journal of Engineering and Management*.
- Thennakoon, A., Bhagyani, C., Premadasa, S., Mihiranga, S., & Kuruwitaarachchi, N. (2019). Real-Time Credit Card Fraud Detection Using Machine Learning. *Confluence*.
- Tyagi, S., Tyagi, A., Rani, S., Kumar, A. S., Adhav, S., & Gupta, S. (2025). The Role of Artificial Intelligence in Risk Management and Fraud Detection in Financial Services. *Journal of Informatics Education and Research*.