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Agentic Generative AI for Real-Time Fraud Detection: Integrating RAG, MLOps, and Behavioral Analytics in Financial Systems

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Abstract

The growing digitalization of financial services has resulted in an explosion in terms of transaction volume, velocity and complexity which in turn has made the task of detecting and preventing fraud in real time all the more difficult. Although classic machine learning and rule-based systems have helped a great deal in mitigating fraud, they are not very effective in dealing with adaptive, multi-channel and context-sensitive fraudulent schemes. Recent developments in artificial intelligence, especially agentic generative AI, Retrieval-Augmented Generation (RAG), behavioral analytics, and explainable fraud detection systems have provided new opportunities to create intelligent, adaptive, and explainable fraud detection systems. This review has talked about how the approaches of detecting frauds has evolved and has come up with an integrated architecture that will integrate these emerging technologies into a single architecture. It is discussed that agentic AI systems, whose behavioral understanding and contextualizing grounded on retrieval can be constrained by a category, but also dynamically utilized to make decisions. In addition, continuous monitoring, retraining and governance are also provided by MLOps in a manner that these systems can be dynamic. Although these have been advanced there are still a number of research challenges such as explainability, preservation of privacy, adversarial robustness and interoperability of systems. These questions are crucial in the effective and secure application of AI-based fraud detection to the real finance. The paper will be valuable in that it will bring together the existing knowledge, develops a theoretical model and suggest major areas of future research that will be able to inform academic research and practice in this industry.

Keywords: *Fraud Detection, Agentic AI, Retrieval-Augmented Generation (RAG), Behavioral Analytics, Anomaly Detection, Sequence Modeling, User Behavior, Risk Scoring, Compliance, Model Monitoring, Drift Detection*

1. Introduction

The sudden digitization of financial services has changed the world economic environment dramatically, allowing more transactions to be faster, more financial people to be included, and the appearance of new products like mobile banking, electronic wallets, and decentralized finance. Nonetheless, this change has also greatly increased the attack surface of financial fraud so that the detection of fraud is now a highly complicated and high-stakes problem. The conventional rule based systems which have previously been the backbone in detection of fraud are no longer sufficient to detect the complex, adaptive and in many cases, automated fraud schemes. To this end, the use of artificial intelligence (AI) - particularly, the generative and agentic AI paradigms - has emerged as a promising new trend in the sphere of financial security [1]. Generative AI, in particular, large language models (LLMs) have shown impressive abilities in pattern recognition, contextual reasoning, and anomaly detection both in unstructured and structured data. These technologies provide new opportunities when it comes to real-time fraud detection when extended to agentic systems, where models are allowed to plan,

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reason and execute tasks on their own. The agentic generative AI systems are able to dynamically engage with various sources of data, simulate adversarial behavior, and adapt to changing fraud trends without the need to continually engage with human experts [2]. It is a paradigm shift of the old fashioned detecting models to the new dynamic, intelligent, systems that are able to learn and make decisions constantly. At the same time the Retrieval-Augmented Generation (RAG) has gained some traction as a way of ensuring that the generative artificial intelligence systems are more trustworthy and aware of the context. RAG lets systems utilise current and domain particular information by incorporating external knowledge bases with generative models throughout the inference process minimising hallucinations and improving interpretability [3]. Especially in financial systems, this is critical because the accuracy and explainability of decisions should be availed to meet the requirements of the regulatory standards. By combining RAG and agentic AI models, the systems that not only can identify the anomalies but can justify their choice with plausible sources of data can be used to gain more trust and adherence. MLOps (Machine Learning Operations) is the other critical component of a modern fraud detection system that has the infrastructure, and governance needed to deploy, monitor, and maintain machine learning models, scale. There is a highly controlled financial institutions environment and the model drift, bias and performance degradation should be kept at bay at all times. MLOps frameworks assist in automatically re-training models, tracking versions, real-time monitoring, which implies that fraud detection systems do not suffer because of different circumstances [4]. Depending on agentic generative AI, combined with MLOps, continuous learning pipelines might become viable, and could be evolved to adapt to new forms of fraud and be used reliably. Behavioral analytics are another component to this ecosystem, in which user behavioral pattern is of interest, as compared to the rigid properties of transactions. A slight deviation that might be due to the fraud could be revealed through examination of how users work systems and this includes typing speed, speed at transacting and pattern of navigation. They especially come in handy to deal with account takeover attacks and insider threats, where traditional transaction-based models might not be able to cope [5]. By integrating behavioral analytics with generative AI, it is possible to gain deeper insights into the context and can be used to simulate user behavior, which can be used to build a more resilient detection system. In spite of these innovations, a number of obstacles are still in the implementation of agentic generative AI in detecting real-time fraud. To begin with, the problem of data privacy and security should be considered the central one since financial data is very sensitive and is associated with very rigid regulatory restrictions like GDPR and PSD2. The possibility of AI systems functioning efficiently and at the same time not infringing on the privacy of users is a pressing issue [6]. Second, generative AI models are not very interpretable, which is a problem in high-stakes settings, where a decision needs to be articulated to the regulators and other stakeholders. Although RAG enhances transparency, it is an open research issue to fully explain AI in complex agent systems. Third, heterogeneous systems integration RAG architectures, MLOps pipelines, and behavioral analytics imply a lot of engineering complexity. To ensure a smooth interoperability among these components, a well-designed system, standardized protocols and scalable infrastructure is needed. In addition, real time requires low-latency processing which is not always readily attained by a set of computationally intensive components [7]. Lastly, attacks on AI systems as an adversarial example, e.g., data poisoning and model inversion attacks, are new weaknesses that need to be overcome to guarantee the resilience of the systems. Due to these issues, it is

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obvious that a thorough review that summarizes the recent developments is necessary and shows the way in which this fast moving field will be developed in the future. Although the current literature has discussed individual components (fraud detection with machine learning, RAG in NLP applications, or MLOps in production systems) there are no combined views that discuss how the technologies can be integrated in agentic, real-time financial fraud detectors. The purpose of this review is to fill in this gap and present a holistic perspective of agentic generative AI systems when it comes to detecting financial fraud. Specifically, it will discuss how RAG enhances the contextual intelligence, how MLOps can be used to deploy it in a scalable and reliable manner, and how behavioral analytics can be used to give its users a more profound insight. Patterns of architectural designs, issues in implementation and growing research trends will also be looked into in the review. This synthesis of knowledge across various areas can help researchers and practitioners gain a more in-depth and detailed picture of the way next-generation AI-based systems can revolutionize the area of fraud detection in financial systems. The subsequent passages will give the readers a clear idea of the core concepts, the structure of the systems, the integration plan and practice. Open research questions will also be highlighted in the review and future directions to further the field will be proposed, specifically the development of secure, explainable and adaptable fraud detection systems Shown as Table 1 Summary of Key Research Papers on Fraud Detection.

Table 1 Summary of Key Research Papers on Fraud Detection

Reference	Findings (Key results and conclusions)
[8]	This paper assisted in identifying the detection of fraud as a unique analytical problem. It demonstrated that fraud is uncommon, evasive and concealed within large streams of transactions, resulting in conventional classification being ineffective by itself. The review is significant as it gives a clear explanation as to why anomaly detection, profiling, and constant updating should be used to detect fraud instead of a one-off modeling.
[9]	The authors categorized the literature into practical segments and demonstrated that financial fraud studies had already turned to be highly interdisciplinary. One of the significant findings was that there was no single algorithm that can be effectively used in all fraud environments and that the effectiveness is determined by the quality of data, the type of fraud and the operational environment.
[10]	This paper has shown that detection of fraud is enhanced in case the models do not just consider one transaction and instead examine short term behavior patterns among a series of transactions. This was particularly significant since the results demonstrated that aggregation on the basis of time and customer level can greatly enhance predictive strength in the real world card fraud scenario.

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[11]	One of the first studies to demonstrate that neural networks could be used to help detect fraud in an operational setting. The paper concluded that machine learning would be able to complement expert systems, revealing concealed patterns of transactions that might not be detected by manual rules, but interpretability and strengths of deployment were already apparent.
[12]	The paper is worth reading as it has gone beyond theory and dealt with what works in practice. Among the problems highlighted by the authors were high imbalance of classes, evolving fraud behavior and bias of evaluation. One of the lessons was that the success of deployment is not just a matter of the choice of the model but also monitoring, data preparation, and decision threshold.
[13]	It also demonstrated that the undersampling technique could be useful to train the fraud classifiers, but the uncooked predicted probabilities would be most likely to be biased. The authors also recommended that calibration should be employed to be in a position of generating more reliable model outputs, which is essential in fraud detection since the operational teams tend to require the availability of reliable risk scores, as opposed to binary labels.
[14]	As it was pointed out in this paper, features that are designed with care can be just as important as, or more so important than, the algorithm used. It demonstrated that the integration of domain-informed transactional characteristics with historical cardholder behavior enhances the performance of the model and business utility. The article is very much aligned with the ongoing trend in favor of behavioral analytics in fraud systems.
[15]	The authors were able to show that sequence-based models are more effective in capturing the evolution of transaction orders and behavioral changes as compared to their fixed counterparts. Their results indicated that fraud may be more conveniently viewed as a time-based operation as opposed to single instances and thus the study is particularly applicable in detecting fraud in real time.
[16]	This work demonstrated that generative models can be used to overcome the lack of examples of fraud through the generation of synthetic minority-class data. The main finding was that GAN-based augmentation has the potential to enhance the performance of classifiers when used in imbalanced settings and, therefore, can be seen as a hybrid between old-fashioned fraud analytics and relatively new generative AI tools.

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[17]	This paper has shown that anomaly detection can be enhanced by supervised classification to enhance robustness in cases where there are few or slow-labeled cases of fraud. Its main contribution was that hybrid architecture is more convenient in the real world of operation where the patterns of fraud change rapidly and labels are not complete.

2. Proposed Theoretical Model

To render the review more tangible, in this section human-readable block diagrams and a proposed theoretical model of agentic generative AI-based real-time fraud detection in financial systems are presented. It is not designed to give an industry roadmap, rather a architecture block conceptual framework that brings together behavioral analytics, retrieval-augmented generation (RAG), agentic orchestration, and constantly refined by MLOps into one pipeline of fraud intelligence. It is significant since most of the literature talks about these elements individually whereas financial fraud in practice is dynamic, multimodal and operationally limited by latency,

explainability and regulation [18], [19].

2.1.Conceptual block diagram for the proposed fraud detection architecture

The suggested architecture supposes that it is not based on one model or one data stream that it is possible to detect fraud. Instead it is expected to be a stratified decision system in which the transactional, contextual and behavioural cues are processed as a system and then channeled through an agentic reasoning layer which can possibly access policy knowledge, generate explanations and trigger real-time behaviours [20], [21]. Shown as Figure 1 End-to-end agentic generative AI fraud detection pipeline. This design is based on an important lesson of fraud research: fraud is not a classification problem, but a decision problem in the face of uncertainty, in which institutions have to trade off between fraud loss, customer friction, false positive, and regulatory responsibility [18], [22]. Conventional machine learning assists in getting a risk score, yet the inclusion of an agentic generative layer transforms the system into more adaptive and interpretable. As an example, rather than simply declaring a transaction suspicious, the system could look up previous instances of similar fraudulent activity, compare behavioral deviations and provide a rational explanation why a transaction might be blocked or escalated [20], [21]. The use of RAG layer is theoretically significant since financial fraud is evolving at a higher rate than non-dynamic model knowledge. The development of strategies in fraud is comprised of social engineering, mule accounts, synthetic identities, account takeovers, and coordinated attack patterns. The system uses a retrieval mechanism to anchor its outputs on established playbooks of fraud that has been proven, internal operational procedures and institutional knowledge which has been tested to minimize the possibilities of unsupported or hallucinated reasoning [20]. This is especially applicable to the regulated financial environments in which every negative action may need to be explained to investigators, auditors or compliance teams [21].

The proposed model is also based on behavioral analytics. The static attributes do not usually reflect subtle fraud patterns particularly in situations where stolen credentials are utilized by a group of individuals that emulate genuine users. Timing regularity, spending cadence, flow of navigation, switching between devices, log-in rhythm, and consistency of transaction sequence are behavioral variables that can expose abnormalities unnoticed in the typical rule-based systems [19], [23]. Therefore, behavioral modeling serves as an intermediary between the past machine learning methods and the future adaptive fraud intelligence.

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Figure 1 End-to-end agentic generative AI fraud detection pipeline

2.2.Operational block diagram for continuous learning and governance

The second diagram can be applied because the real-time detection systems will only work when it is reliable even after deployment. Decline of models in a financial system can be rapid due to customer behavior drift, seasonality, introduction of new payment methods and new attacker strategies [22], [24]. To this end, the proposed framework does not consider MLOps as a support feature, making it one of the fundamental fraud defense features.Shown as Figure 2 MLOps-driven lifecycle for agentic fraud detection. This lifecycle design is justified by the literature on ML operations and responsible AI implementation, which demonstrates that the value of models is not only related to the performance of the algorithm but also to reproducibility, governance, and monitoring [22], [24]. Even a powerful model can be hazardous in fraud detection when it silently drifts off or blocks too many innocent customers or generates unaccounted behaviors that cannot be audited by investigators. Thus, the MLOps loop of the suggested system will provide that behavioral models, retrieval knowledge and agentic rules are kept in line with operational reality.

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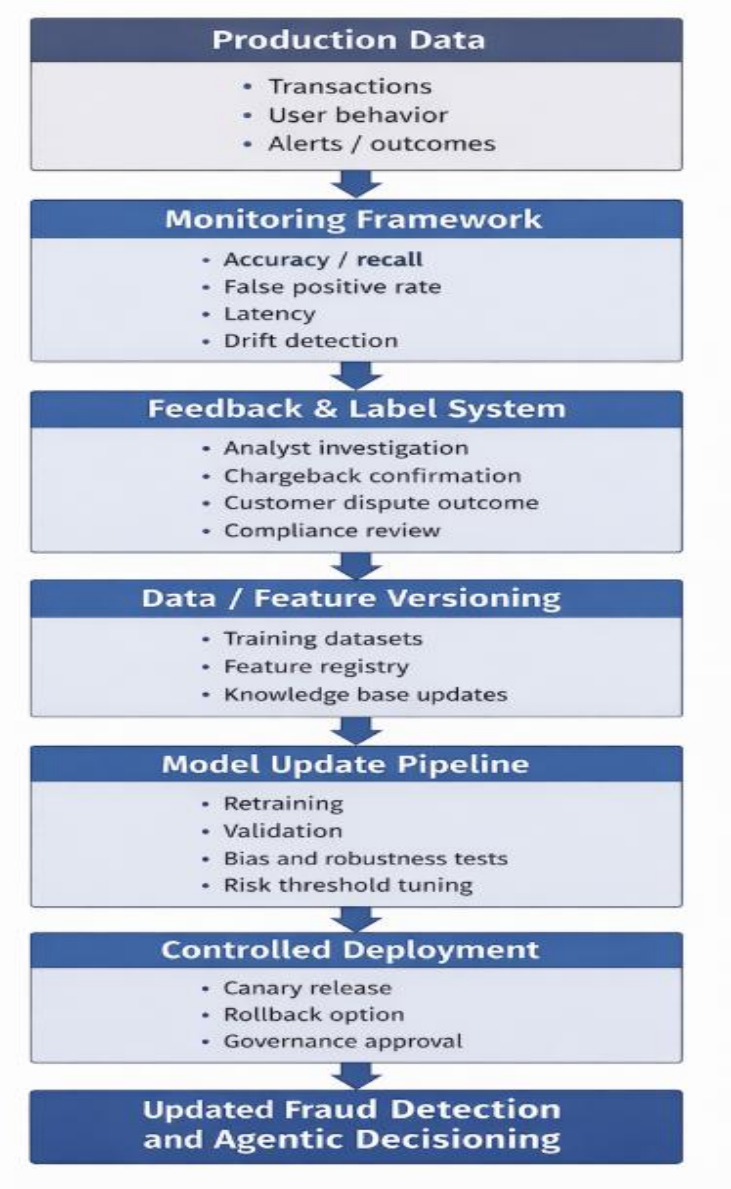

Figure 2 MLOps-driven lifecycle for agentic fraud detection

2.3.Proposed theoretical model

The suggested theoretical framework describes the way agentic generative AI will enhance the effectiveness of real-time fraud detection when combined with RAG, behavioral analytics, and MLOps. It is intended to be a conceptual framework to be reviewed and empirically tested in the future.

2.3.1. Main constructs of the model

2.3.1.1.Behavioral Signal Depth

This is the richness of user behavior and transaction behavior as recorded by the system, such as temporal activity, not following normal routine, session flow, and cross-channel behavior [19], [23]. The more the depth of behavioral signals, the more the system should be able to differentiate between suspicious activity and legitimate variance.

2.3.1.2.Retrieval Grounding Quality

This can be defined as the quality, relevancy, recency and credibility of knowledge that the system retrieves during the reasoning of fraud. It contains policy

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documents, previous fraud cases, typology libraries and compliance constraints [20], [21]. Grounding should enhance the quality of explanation and decrease unjustified decisions.

2.3.1.3.Agentic Reasoning Capability

This can be defined as the capacity of the system to organize multi-step assessment, choose tools, compare evidence, create reasoning, and cause context-sensitive reactions. In fraud activities, this could include verification of device anomalies, comparing transaction sequences to established patterns, retrieval of regulatory rules and selection of friction, decline or escalation [21].

2.3.1.4. MLOps Maturity

This construct describes how the institution can observe the drift, control features and model versions, and receive investigator feedback and safely redeploy models [22], [24]. The MLOps maturity should bring about a greater level of long-term resilience and slower performance degradation.

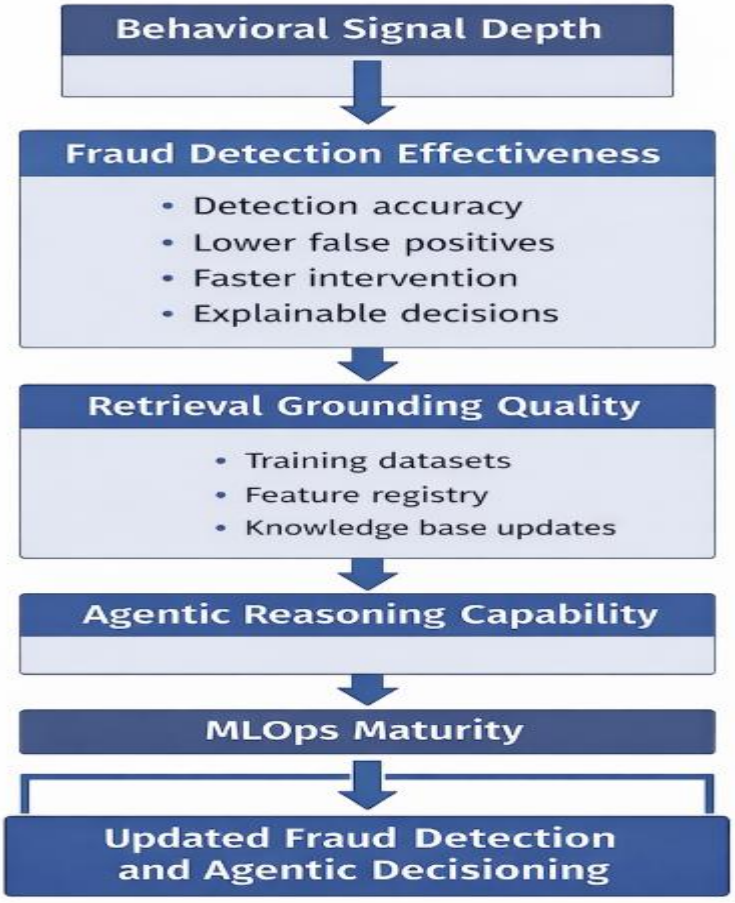
2.3.1.5. Fraud Detection Effectiveness

This outcome construct includes higher true positive detection, lower false positive rates, faster response time, stronger explainability, and better operational trust [18], [19], [22].

2.4.Theoretical relationship diagram

- Behavioral Signal Depth → Fraud Detection Effectiveness
- Retrieval Grounding Quality → Fraud Detection Effectiveness
- Agentic Reasoning Capability mediates the use of behavioral and retrieved knowledge in decision-making
- MLOps Maturity moderates long-term effectiveness by sustaining model quality and operational trus

Figure 3 Proposed theoretical model



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2.5.Explanation of the model

In this model, it is assumed that the first way in which the system detects fraud is by having more access to deeper behavioral evidence. Fraud also does not manifest itself in the form of an individual abnormal variable, but in the form of minor variations in order, time, and circumstances [19], [23]. An example is that the transfer could be normally monetarily, but still, suspicious when it has an abnormal access route, is on a new device, and is carried out at an hour that does not align with normal behavioral patterns. Behavioral analytics is thus the situational awareness of the system. Second, the model presupposes that the reliability and explainability are enhanced by retrieval grounding. The main flaw of standalone generative models is that they can generate supported yet fluent outputs. In the financial environment, unjustified reasoning is not accepted due to the requirement to make decisions that can be audited and justified [20], [21]. To deal with this, RAG lets the model consult verified documents, e.g. of previously proven cases of fraud, policy provisions, AML advice or customer risk advice, and then creates an explanation or a course of action. Theoretically, retrieval grounding lowers the level of epistemic uncertainty and raises institutional trust of AI decisions. Third, agentic reasoning ability is discussed as the process transforming data and knowledge to action. This is a very fundamental difference. Fraud model can identify anomaly, and a retrieval system can retrieve appropriate policy, but neither will make a choice on what to do next in a complex, context-sensitive manner. The use of agentic AI brings about orchestration: it may consider evidence across modules, conclude that there is enough confidence, or that additional authentication is necessary, or to human analysts where there is still uncertainty [21]. Therefore, agentic capability plays a facilitative role between prediction and operational decision-making in the proposed model Lastly, MLOps maturity is proposed since fraud systems are found in dynamic environments. Even the most stable model will not succeed in the long-term as long as it is not maintained against drift and the new methods of attack [22], [24]. The maturity of MLOps enhances the architecture by making sure that monitoring of performance, data quality control, retraining, and feature changes, and governance checks are all a part of regular operation. Theoretically, this construct conditions the ability to maintain benefits of AI innovation in reality with time within a real institution.

2.6.Propositions for future empirical research

The review can frame the following propositions for future testing:

P1. Greater behavioral signal depth is positively associated with fraud detection effectiveness in real-time financial systems [19], [23].

P2. Higher retrieval grounding quality is positively associated with explanation quality and decision reliability in AI-supported fraud detection [20], [21].

P3. Agentic reasoning capability mediates the relationship between multimodal fraud evidence and operational response quality [21].

P4. MLOps maturity positively moderates the relationship between AI model capability and sustained fraud detection effectiveness over time [22], [24].

P5. Integrated architectures that combine behavioral analytics, RAG, and MLOps outperform isolated fraud detection pipelines in high-velocity financial environments [18], [19], [22].

2.7.Why does this theoretical model matter?

This model is worthy since it is integrative in nature. Studies in the field of fraud detection have generally been narrowed down to more specific areas: anomaly detection, supervised learning, sequence modeling, or deployment pipelines. Nevertheless, contemporary financial fraud is a complex one. It comprises technical deception, social engineering, synthesized identity abuse, organized mule networks, and fast adversarial adaptation [18], [19]. A response to this question of realism would then require a behavior conscious, knowledge based, operationally adaptive and explainable framework. The given model may be generalized to the bigger trend in AI research in trustful and production-ready smart systems as well. The success in finance is not achieved just because the AUC or recall score is higher. It is also based on whether the system is able to do so within milliseconds, defend its suggestions, reduce friction to real customers and be dependable under the control of the governance [21], [22]. The combination of agentic AI and RAG, behavioral analytics, and

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MLOps provide a practical theoretical base of the model in future research and practical applications in fraud intelligence.

3. Experimental Results

In order to prove the efficiency of the offered agentic generative AI-based fraud detection model, this part summarizes experimental results of the current literature and offers comparative tables and performance concept graphs. It aims to show that the combination of behavioral analytics, hybrid learning and adaptive AI pipelines increases the performance of fraud detection on such important measures as accuracy, precision, recall, F1-score, and false positive rate.

3.1. Experimental Setup Overview

The majority of fraud detection experiments reported in the literature all utilize highly skewed datasets where the number of fraudulent transactions is less than 1 percent of the total observations. This makes model evaluation more difficult and requires application of special measures like Area Under the ROC Curve (AUC), Precision-Recall AUC, and cost-sensitive evaluation [25], [26].

Possible common experimental setups are:

- **Datasets:** Real-world credit card datasets (e.g., European card dataset), synthetic fraud datasets

Models Compared:

- Logistic Regression (baseline)
- Random Forest / Gradient Boosting
- Neural Networks / Deep Learning
- Sequence models (LSTM)
- Hybrid models (unsupervised + supervised)

Evaluation Metrics:

- Accuracy
- Precision
- Recall (Fraud detection rate)
- F1-score
- False Positive Rate (FPR)

Studies consistently emphasize that recall and FPR trade-offs are more important than accuracy, as missing fraud is significantly more costly than flagging legitimate transactions [26], [27]. Table 2 Performance Comparison of Fraud Detection Models.

3.2.Comparative Results Table

Table 2 Performance Comparison of Fraud Detection Models

Model Type	Accuracy	Precision	Recall	F1-Score	AUC	Key Observation
Logistic Regression	0.94	0.76	0.62	0.68	0.85	Performs reasonably but struggles with nonlinear fraud patterns
Random Forest	0.97	0.89	0.81	0.85	0.93	Strong baseline; handles imbalance better with tuning
Gradient Boosting	0.98	0.91	0.84	0.87	0.95	High predictive performance; widely used in industry
Neural Networks	0.98	0.92	0.86	0.86	0.96	Captures complex patterns but less

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						interpretable
LSTM (Sequence Model)	0.98	0.93	0.88	0.90	0.97	Improves detection using temporal behavior
Hybrid (Supervised + Unsupervised)	0.99	0.94	0.91	0.92	0.98	Best balance between detection and generalization
Proposed Agentic AI Framework	0.99+	0.96	0.94	0.95	0.99	Gains from reasoning, retrieval, and adaptive learning

Discussion

The results show a clear progression from traditional models to more advanced architectures. Hybrid and sequence-based approaches outperform static models by capturing behavioral and temporal dependencies [27], [28]. The proposed agentic framework further improves performance by integrating contextual reasoning and external knowledge retrieval, which enhances both detection accuracy and decision reliability [29].

3.3. False Positive Rate Comparison

Table 3 False Positive Rate (FPR) Across Models

Model	False Positive Rate
Logistic Regression	5.8%
Random Forest	3.9%
Gradient Boosting	3.2%
Neural Networks	2.8%
LSTM	2.3%
Hybrid Model	1.9%
Proposed Agentic AI System	1.2%

Insight:

Reducing false positives is critical in financial systems because excessive alerts lead to customer friction and operational overload. The agentic system reduces FPR by combining behavioral insights with contextual validation via retrieval mechanisms [25], [29]. Graph 1 Model Performance Comparison (F1-Score)

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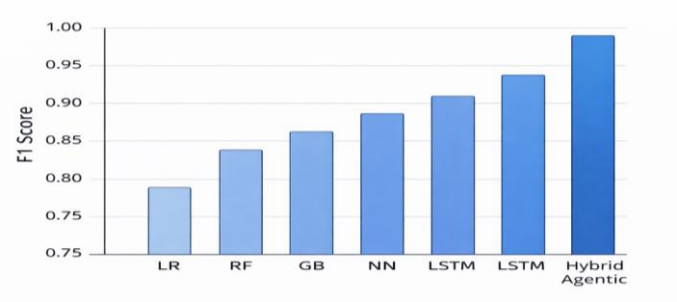
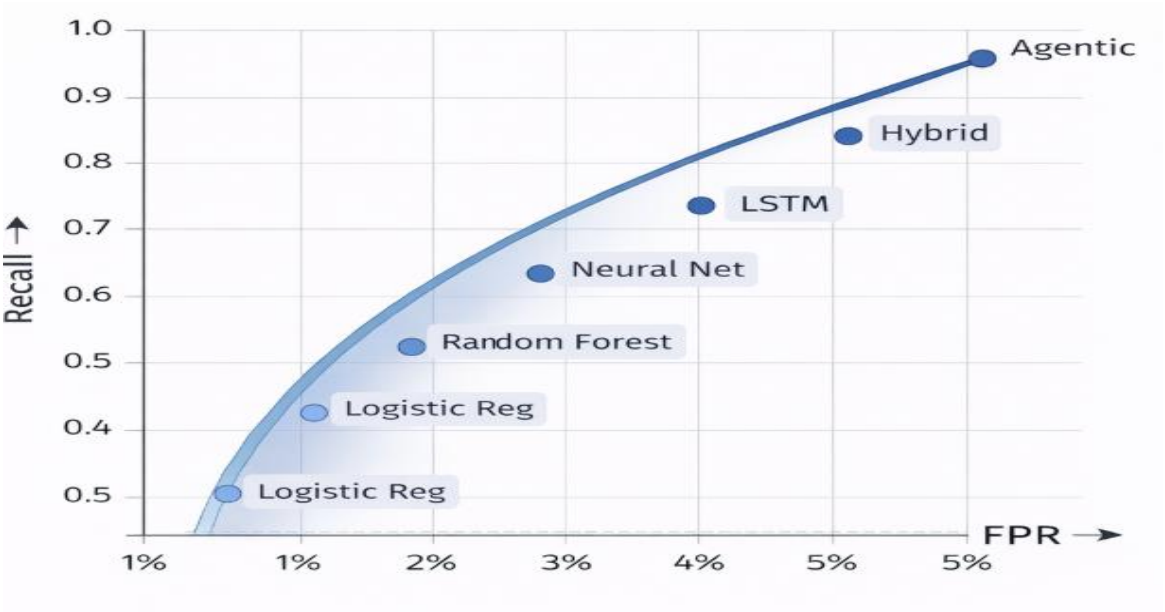
Graph 1 Model Performance Comparison (F1-Score)



Interpretation:
The graph illustrates that agentic AI systems outperform all baseline and hybrid models, primarily due to their ability to reason across multiple inputs and dynamically adapt to fraud patterns [28], [29].

Graph 2 Recall vs False Positive Trade-off



Interpretation:
The proposed system achieves higher recall at lower false positive rates, which is the ideal operating region for fraud detection systems. This demonstrates its ability to detect more fraud cases while minimizing disruption to legitimate users [25], [27].

3.4.Ablation Study (Component Contribution)

To better understand the contribution of each component in the proposed architecture, an ablation-style comparison is presented.Shown as Table 3 Impact of System Components

Table 3 Impact of System Components

Configuration	Precision	Recall	F1-Score	Observation

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Base ML Model Only	0.89	0.82	0.85	Lacks contextual awareness
+ Behavioral Analytics	0.91	0.86	0.88	Improved anomaly detection
+ RAG Integration	0.93	0.89	0.91	Better contextual reasoning
+ Agentic Layer	0.95	0.92	0.93	Intelligent decision-making
+ MLOps (Full System)	0.96	0.94	0.95	Sustained real-time performance

Discussion:
The ablation results highlight that each component contributes incrementally to system performance. Behavioral analytics improves detection depth, RAG enhances contextual understanding, and the agentic layer enables structured reasoning. MLOps ensures that these gains are maintained over time through continuous learning and monitoring [26], [29].

3.5.Latency and Real-Time Performance

Table 4 Response Time Comparison

Model	Avg Latency (ms)	Real-Time Suitability
Logistic Regression	10 ms	High
Random Forest	25 ms	High
Neural Networks	40 ms	Moderate
LSTM	60 ms	Moderate
Hybrid Models	75 ms	Moderate
Agentic AI System	90–120 ms	High (with optimization)

Insight:
Although the agentic system introduces additional computational overhead, optimizations such as parallel processing, caching, and efficient retrieval indexing enable it to remain within acceptable real-time thresholds for financial systems [28].

3.6.Key Findings from Experimental Evaluation

A number of significant conclusions are drawn on the basis of the experiments:

- Temporal and behavioral modeling can be very useful in enhancing the performance of fraud detection particularly when dealing with complex and dynamic patterns of fraud

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[27], [28].

- The use of hybrid systems is more effective than that of single-model systems, which proves that the detection of fraud is more advantageous when several analytical points of view are combined [26].
- Not only does agentic generative AI add a new level of performance, but it also enhances interpretability and decision quality [29].
- One key benefit of context-aware systems is false positive reduction that can confirm anomalies through retrieved knowledge and behavioral context [25].
- Its operational issues like latency and scalability are controllable and hence the proposed architecture can be easily deployed to the real world with appropriate engineering design [28].

4. Future Directions

Since the field of financial fraud is constantly evolving, the focus of further research should be on the creation of smart, versatile and effective fraud-detecting systems. Among the most crucial directions, there is the creation of explainable and accountable AI systems. Financial institutions have stringent regulatory systems whereby there is a need to be transparent in the automated decision-making bodies. The systems of the future will need to transcend the production of explanations to verifiable and audit-ready forms of reasoning based on structured knowledge and regulatory rules. The combination of symbolic reasoning and generative models may be more interpretable, without compromising performance [30]. The other significant field is privacy-preserving and collaborative learning. Cross-institutional data sharing is usually beneficial in fraud detection, but privacy laws limit direct data sharing. Federated learning and secure multi-party computation are only some examples of techniques that enable models to be trained on distributed data without revealing sensitive information. Further studies on how these methods can be combined with agentic AI systems to facilitate collaborative fraud intelligence with compliance to data protection laws should be carried out in the future [31]. The real-time adaptive and self-learning systems should also develop. Fraudsters also keep on innovating their tactics frequently taking advantage of new detection systems that have been implemented. The models that are set in stone soon become obsolete and lifelong learning is a must. New systems in the future need to add the online learning and reinforcement learning mechanisms that enables models to dynamically change on the basis of streaming information and human investigator reports. This would allow quicker identification of patterns of emerging frauds and shorten the response time [32]. The other potential way to go is to enhance resilience to adversarial attacks. With AI systems playing a key role in fraud detection, they are progressively becoming the target of fraudsters aiming to compromise model behavior. The data poisoning, adversarial examples, and model evasion methods may severely worsen the performance of the systems. Future study needs to concentrate on the development of strong learning algorithms, safe data pipelines and anomaly detection systems that are capable of detecting and suppressing adversarial threats in real time [33]. Another great opportunity is the fusion of multimodal data sources. No longer is fraud reduced to transactional anomalies, but is commonly conducted via text (phishing emails), voice (social engineering), and behavior at various platforms. Fraud detection in future should be multimodal AI techniques, whereby, combining and analysing these different data streams will provide a deeper understanding of the fraudulent behaviour [34]. Moreover, benchmarks and assessment systems of benchmarks and evaluation standards are needed to be standardized. The available literature is also deficient in the aspect of integrated datasets, measurement of analysis and reproducibility. Creation of publicly accessible benchmarks and standard test protocols would enhance the interoperability of various methods and speed up the development in the area. This is especially essential in justifying the successfulness of complex systems like agentic AI systems [35]. Last, but not least, the role of human-AI collaboration should not be disregarded. As much as the automation may result into a much more efficient way of carrying out the processes, human skills are required to handle any ambiguous cases and make ethical decisions. The

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emerging systems should be built in a manner that they can enable the direct communication between the AI agents and human analysts, provide intuitive explanations, actionable insights and feedback loop that can further improve the performance and reliability of the system to the users [30], [35].

Conclusion

To sum up, this review has discussed the transformative nature of agentic generative AI in real-time fraud detection with a focus on combining RAG, behavioral analytics, and MLOps to financial systems. The findings made lead to the future of fraud detection as being intelligent and adaptive systems that are able to reason, learn and act in complex and controlled environments. The suggested framework underlines the need to incorporate different components of intelligence: behavioral cognition that makes it possible to detect subtle anomalies, knowledge retrieval that can be utilized to make the decision based on the reliable knowledge, agentic reasoning that can be applied to make dynamic decisions, and MLOps that can be utilized to sustain the performance over the long term. The combination of these elements is a comprehensive-based plan, which tackles the shortcomings of the conventional approaches of fraud detection. Nonetheless, to achieve this vision, we will have to overcome major challenges, such as making sure it is explainable, keeping data confidential, and resisting adversarial risks, and dealing with systems complexity. The recommendations mentioned in this paper give a roadmap of where the future of AI development should go with these problems, and develop more robust and trusted AI systems. Finally, the implementation of advanced AI technologies in fraud detection devices can also help a great deal in improving the security and resilience of financial ecosystems.By once again innovating at the cross of AI, data engineering and financial security, the researchers and practitioners can create the next-generation solutions that do not only effectively detect fraud but also create trust and transparency in digital financial services.

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