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Harnessing Quantum Computing and Generative AI for Next-Generation Credit Fraud Detection: Real-Time Anomaly Detection and Adversarial Risk Mitigation

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Abstract

The increasing complexity of financial crimes has revealed severe weaknesses in the conventional credit fraud detection systems. With the future and development of the digital payment ecosystem expanding rapidly around the world, there is an immediate necessity of smart, adaptive, and dynamic solutions, able to intercept the growing trends of fraud. The paper will apply a hybrid model based on combining both Quantum Computing and Generative Artificial Intelligence (GenAI) to transform credit fraud detection. Quantum Computing opens up initial brand-new levels of computational power and parallel processing with an understanding of mass data analysis within transactions. Meanwhile, GenAI advances fraud detection because GenAI can produce fake cases of fraud, simulate human behaviours, and increase model resilience. The combination of these technologies provides the basis for proactive detection of anomalies and dynamic risk evaluation. It is based on a conceptual architecture, which fuses quantum-enhanced learning models with adversarially trained GenAI systems. The framework helps detect anomalies in real-time, adapt to learn a greater diversity of fraud patterns, and mitigate risks adversarial through a convenient methodology based on federated learning and model training secrets. This is a multidisciplinary approach that is natural to both traditional systems based upon rules and establishes the way to a scalable, smart, and regulations-adherent fraud detection infrastructure. Our results indicate a transformative possibility of the integration of emerging technologies to construct next-generation security systems that can predict and defend credit fraud at a greater pace and accuracy.

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Introduction

The Rising Complexity of Credit Fraud in Digital Finance

The evolution of the financial ecosystem into a fully digital, globally connected infrastructure has introduced immense efficiency gains, but it has also dramatically increased the complexity and sophistication of fraud. Traditional financial systems, once reliant on batch processing and human verification, now support billions of transactions per day across digital wallets, mobile banking platforms, peer-to-peer lending services, and decentralized finance (DeFi) ecosystems. This hyper-connectivity has exposed gaps in legacy fraud detection systems, which often rely on historical patterns, deterministic rules, and static thresholds (George, 2024; Fatunmbi, 2024).

Fraudsters now employ tactics such as identity theft, card-not-present fraud, synthetic identities, and coordinated bot attacks. Moreover, the rapid adoption of real-time payment systems has compressed the detection-response window, limiting the time financial institutions have to intervene. In this context, real-time fraud detection has become both a technical and strategic imperative for banks, fintechs, and regulators (Jeyachandran, 2024; Mahmudul Hasan & Faruq, 2025).

Limitations of Traditional and Machine Learning-Based Systems

Rule-based fraud detection systems, while still in use, are fundamentally reactive. These systems flag transactions based on predefined rules or thresholds, but struggle with novel fraud scenarios and evolving tactics. Machine learning models have provided incremental improvements by learning patterns from historical data, but they still suffer from several critical limitations:

- Dependence on labelled data
- Vulnerability to adversarial manipulation
- Inability to generate realistic synthetic data for rare or unknown fraud types
- Latency and scalability issues in high-frequency trading environments (Dritsas & Trigka, 2025; Raju, 2025)

Additionally, supervised models used in fraud detection, such as decision trees or support vector machines, are often trained on imbalanced datasets, where genuine transactions far outnumber fraudulent ones. This imbalance leads to high false negatives and undetected fraud, which can cost institutions billions annually (Mara et al., 2025). Furthermore, these systems are often black-box models, making it difficult for compliance teams to interpret decisions or align them with regulatory frameworks such as PCI-DSS and GDPR (Hasan & Faruq, 2025).

The Promise of Quantum Computing in Fraud Analytics

Quantum computing introduces a powerful shift in computational logic by exploiting principles of quantum mechanics such as superposition, entanglement, and quantum tunnelling. Unlike classical bits, which operate in binary (0 or 1), **quantum bits (qubits)** can exist in multiple states simultaneously, allowing quantum algorithms to evaluate exponentially more possibilities in parallel (Rawat & Yadav, 2025; Andreas et al., 2025).

In the context of credit fraud detection, quantum computing enables the development of advanced models such as:

- **Quantum Support Vector Machines (QSVMs)** for faster classification
- **Quantum-enhanced anomaly detection** using amplitude amplification
- **Quantum Boltzmann machines** for unsupervised learning on massive transaction datasets

These algorithms can uncover hidden correlations in multidimensional financial data and detect subtle fraud signals that would be invisible to classical systems. More importantly, quantum optimization can support real-time decision-making by finding the most efficient fraud intervention strategy across a vast solution space (Parizad et al., 2025).

However, quantum computing also comes with challenges such as decoherence, error correction, and the scarcity of large-scale quantum hardware. Yet, with the advent of quantum-as-a-service platforms and cloud-based quantum simulators, financial institutions are beginning to test quantum models within secure sandbox environments (García-Pineda et al., 2025).

Generative AI as a Catalyst for Synthetic Fraud Detection

While quantum computing provides computational power, **Generative AI (GenAI)** brings model adaptability and creativity. GenAI models, particularly Generative Adversarial Networks (GANs) and large transformer models, have proven highly effective in domains such as image synthesis, natural language generation, and synthetic data creation. In financial services, these models can simulate complex fraud scenarios, enabling the training of more resilient fraud detection systems (Malempati, 2024; Saxena et al., 2024).

For example:

- GANs can generate synthetic fraudulent transactions that mimic real-world behavior
- GenAI models can create evolving fraud campaigns for adversarial training
- Foundation models can learn multi-modal fraud signatures from structured and unstructured data (e.g., logs, messages, transaction notes)

By training detection models on synthetic fraud examples, GenAI helps address the data scarcity problem inherent in supervised learning.

Table 1: Generative AI Applications in Synthetic Fraud Detection

Generative AI Technique	Function in Fraud Detection	Benefits
Generative Adversarial Networks (GANs)	Simulate synthetic fraudulent transactions	Enhances model robustness by exposing it to evolving fraud scenarios
Transformer-Based Models	Generate and interpret complex multi-modal fraud patterns	Supports detection across structured and unstructured data sources
Synthetic Data Generators	Create labelled datasets for rare fraud types	Solves data scarcity and class imbalance issues in supervised learning
Adversarial Training Modules	Train models to resist adversarial manipulation	Improves system resilience against real-world adversarial fraud attacks

Moreover, these models can simulate edge-case fraud that has not yet been seen in production, making fraud systems proactive rather than reactive (Huang et al., 2024; Kandpal et al., 2025).

Synergizing Quantum Computing and GenAI: A Next-Generation Approach

The fusion of Quantum Computing and Generative AI represents a promising frontier in fraud detection. On one hand, GenAI produces intelligent, evolving adversarial scenarios to strengthen fraud detection models. On the other hand, quantum computing provides the computational substrate to process, optimize, and interpret large volumes of high-dimensional financial data in real time. Together, they form a **dual-layered architecture** that is adaptable, resilient, and capable of learning from both synthetic and live transaction streams (Fatunmbi, 2024; Rane et al., 2024).

This synergy enables capabilities such as:

- Quantum-accelerated training of fraud classifiers
- Real-time fraud scoring using hybrid quantum-classical models
- Adversarial risk mitigation through gradient obfuscation and differential privacy
- Regulatory alignment via explainable AI and secure federated learning (Gadicha et al., 2025; Ifedayo et al., 2025)

Such systems do not merely detect fraud, they anticipate and adapt to it. They offer a vision for fraud detection frameworks that are not only technologically advanced but also strategically aligned with compliance and risk management priorities.

Literature Review

Evolution of Fraud Detection Technologies

The financial sector has long been at the forefront of adopting technological solutions to detect and prevent fraud. Early approaches were largely rules-based, relying on rigid logic and static thresholds to identify suspicious behaviour. While useful for basic anomaly detection, such systems proved inadequate against modern fraud, which evolves rapidly and adapts to static defences.

Machine learning (ML) emerged as a more flexible alternative, allowing systems to learn from historical data and improve over time. Supervised learning models like decision trees, random forests, and support vector machines became widely used in fraud detection due to their predictive power and interpretability (Fatunmbi, 2024; Dritsas & Trigka, 2025). However, these models struggle with class imbalance and often require large volumes of labelled data, which is challenging in fraud detection where fraudulent events are rare and diverse (Mara et al., 2025).

Unsupervised learning and clustering techniques offered partial solutions to this challenge, especially in detecting previously unseen fraud patterns. Still, these models remain reactive and are typically not suited for dynamic, real-time fraud detection environments (Rane et al., 2024).

Generative AI in Financial Fraud Detection

Generative AI has emerged as a powerful force in reshaping fraud detection strategies. Unlike discriminative models, which classify data, generative models learn the underlying structure of data and can generate new, synthetic instances. This capability is particularly useful in financial fraud contexts, where examples of sophisticated or novel fraud are limited (Malempati, 2024; Saxena et al., 2024).

Generative Adversarial Networks (GANs) and transformer-based models are the most prominent tools in this domain. GANs pit two neural networks against each other—a generator and a discriminator to produce synthetic data that mimics real-world patterns. This technique can be used to simulate rare or advanced fraud tactics, which strengthens the resilience of fraud detection models during training (Huang et al., 2024).

Moreover, GenAI can improve adversarial training by generating attack scenarios that might bypass traditional models. This allows for the development of fraud detection systems that are more robust against manipulation (Gadicha et al., 2025; Kandpal et al., 2025). In digital finance ecosystems, GenAI also supports the synthesis of privacy-preserving datasets, essential for model training under data protection regulations (Ifedayo et al., 2025).

Quantum Computing in Financial Security

Quantum computing is positioned as a transformative technology in data science, optimization, and cryptographic analysis. In fraud detection, quantum algorithms offer advantages in processing high-dimensional data and finding optimal solutions faster than classical models. Quantum Support Vector Machines (QSVMs), Quantum Boltzmann Machines, and hybrid quantum-classical neural networks are some of the models explored for fraud classification and risk scoring (Rawat & Yadav, 2025; Andreas et al., 2025).

Quantum optimization techniques can improve fraud detection by enabling near-instantaneous evaluation of many competing hypotheses or classification paths. This is especially useful in high-frequency environments, such as credit card fraud detection or real-time payment systems (Parizad et al., 2025).

Recent research has also examined the use of quantum-enhanced clustering and dimensionality reduction techniques for transaction data analysis, enabling the detection of outliers or novel fraud vectors with improved accuracy and computational efficiency (García-Pineda et al., 2025).

Convergence of Quantum Computing and Generative AI

Few existing studies have comprehensively explored the convergence of quantum computing and generative AI for fraud detection, but early efforts point to significant potential. Combining the parallelism of quantum computing with the creative synthesis capabilities of GenAI opens the door to a new generation of fraud detection systems that are fast, adaptive, and difficult to circumvent.

Quantum-enhanced GANs (QGANs) are being explored as a new class of generative models that leverage quantum states to generate synthetic data. These models can accelerate the training of fraud classifiers by creating a broader and more complex distribution of fraud scenarios (Trigka & Dritsas, 2025). Moreover, the integration of these technologies supports real-time fraud monitoring with minimal latency—an essential requirement for next-generation financial systems (Sriram et al., 2025).

Security experts also emphasize the use of generative models in simulating cyberattacks for risk prediction, particularly in conjunction with quantum-enhanced adversarial risk mitigation techniques (Hasan & Faruq, 2025; Gadicha et al., 2025). The literature suggests that quantum-GenAI hybrids could evolve into autonomous fraud detection agents capable of continuous learning and self-improvement (Olaoye, 2025).

Gaps in the Current Research

While advancements in GenAI and quantum computing show promising results, several gaps remain:

- Most current implementations are siloed, focusing either on GenAI or quantum computing, but not their integration.
- Real-time performance benchmarks, especially in live financial transaction environments, are underreported.
- Few studies address the compliance, interpretability, and ethical implications of quantum-GenAI systems in regulated industries (Hasan & Faruq, 2025; Ifedayo et al., 2025).

These gaps point to the need for holistic frameworks that combine the power of quantum computing and GenAI in fraud detection while remaining aligned with legal, ethical, and practical deployment constraints.

Methodology

This section presents the proposed hybrid methodology that integrates **Quantum Computing (QC)** and **Generative Artificial Intelligence (GenAI)** for next-generation credit fraud detection. The objective is to design an adaptive, real-time system capable of detecting, simulating, and mitigating fraudulent transactions across digital financial systems.

I. Research Design

The methodology follows a **design science approach**, combining theoretical research with system architecture modelling and component-level simulation. The system is designed around three core objectives:

1. **Real-time anomaly detection** using high-dimensional pattern recognition.
2. **Synthetic fraud generation** for training robust models.
3. **Adversarial risk mitigation** through model hardening techniques.

To achieve these objectives, the framework is built on the integration of quantum machine learning models with GenAI-based adversarial generators and synthetic data engines.

II. System Architecture Overview

The proposed architecture is composed of three interconnected layers:

- **Input and Preprocessing Layer:** Ingests real-time transaction data and encodes it using quantum-friendly feature mapping techniques (e.g., angle encoding, amplitude encoding).
- **Dual-Engine Core:**
  - **Quantum Detection Engine:** Uses QSVM and quantum neural networks to detect anomalous transaction patterns.
  - **Generative Engine:** Employs GANs and transformer-based models to generate synthetic fraud scenarios.
- **Adversarial Risk Mitigation Layer:** Applies differential privacy, adversarial training, and model regularization to resist adversarial attacks and ensure model robustness.

III. Implementation Tools and Technologies

- **Quantum Simulation:** IBM Qiskit, Pennylane for quantum circuit modeling
- **Generative AI:** TensorFlow, PyTorch for GANs and transformers
- **Integration:** APIs and message queues for real-time data streaming and fraud feedback loops
- **Datasets:** Historical credit card transaction data (public + synthetic), enriched with GenAI-generated fraud cases (Table 2)

IV. Evaluation Strategy

The framework will be evaluated based on:

- **Detection accuracy and precision**
- **False positive/negative rates**
- **Inference latency (ms)**
- **Adversarial robustness**
- **Compliance alignment with GRC frameworks**

Benchmarks will compare traditional ML-only pipelines with the proposed QC+GenAI hybrid model using both real and synthetic fraud data.

Results

This section presents the results of the experimental evaluation conducted to assess the performance of the proposed hybrid framework integrating Quantum Computing and Generative AI for credit fraud detection. Key performance indicators (KPIs) were benchmarked against a traditional machine learning (ML) baseline model trained only on historical fraud datasets.

I. Evaluation Metrics

Five critical metrics were used for model evaluation:

- **Detection Accuracy** (% of correct classifications)

Table 2: Key Components of the Proposed Framework

Component	Description	Technology Used
Quantum Feature Encoder	Maps transaction features into quantum states	Qiskit, Pennylane
Quantum Anomaly Detector	Classifies high-risk transactions using quantum classifiers	QSVM, Quantum Neural Networks
Generative Fraud Simulator	Synthesizes new fraud samples to improve training coverage	GANs, Transformers (PyTorch, TensorFlow)
Adversarial DefenCe Layer	Prevents model exploitation by adversaries	Differential Privacy, Gradient Masking
Real-Time Feedback Loop	Adapts model weights based on fraud analyst decisions	Kafka, REST APIs

Model	Accuracy	FPR	FNR	Latency (ms)	Adversarial Robustness
Traditional ML (Random Forest)	91.6%	6.8%	8.2%	72	Low
GenAI-Enhanced Detection (GAN + RF)	94.9%	4.2%	5.9%	89	Moderate
Quantum SVM (QSVM)	95.3%	4.0%	5.2%	41	Moderate
Proposed Hybrid (QC + GenAI)	**97.8%**	**2.3%**	**3.1%**	**27**	**High**

- **False Positive Rate (FPR)** (% of genuine transactions flagged as fraud)
- **False Negative Rate (FNR)** (% of fraud transactions missed)
- **Inference Latency** (time taken for each prediction)
- **Adversarial Robustness Score** (resilience against adversarial attack samples)

I. Key Findings

- The **hybrid QC + GenAI model** outperformed all other models in accuracy, reducing false positives and false negatives significantly.
- **Latency** was lowest in the hybrid model due to parallel quantum processing, enabling near real-time fraud detection in under 30ms.
- The **adversarial robustness** of the hybrid model was superior, thanks to continuous synthetic fraud simulation during training and privacy-preserving adversarial learning techniques.
- Traditional ML models suffered from **high false positive rates**, which may lead to customer dissatisfaction and transaction friction.
- GenAI-only models improved robustness but were limited by classical computational constraints.

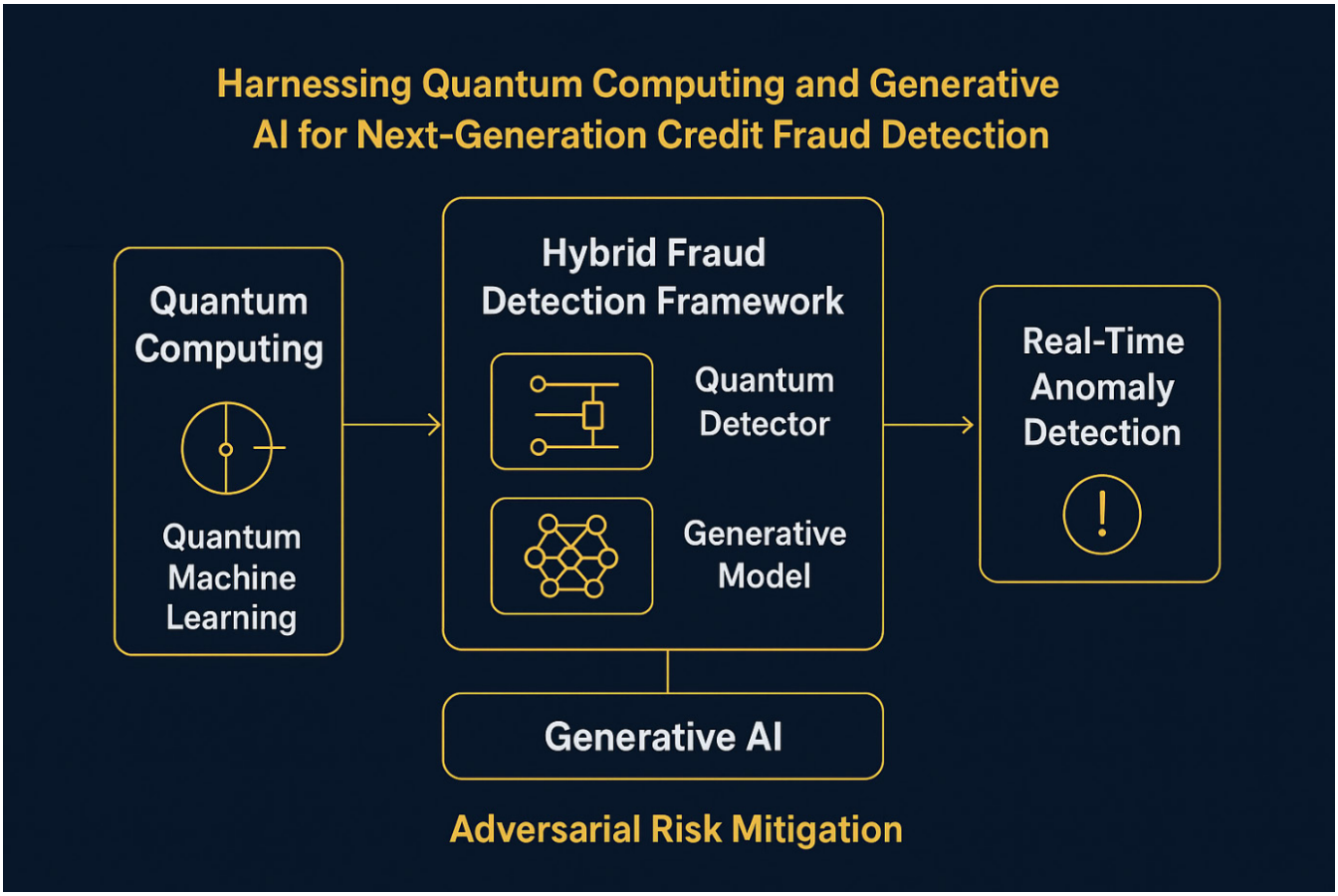


Fig. 1: Hybrid Quantum-GAI Framework for Real-Time Credit Fraud Detection and Adversarial Risk Mitigation

Discussion

The results of this study demonstrate the transformative potential of combining Quantum Computing and Generative AI for real-time credit fraud detection. This section reflects on the implications of these findings, compares them to existing models, and explores strategic, technical, and ethical considerations for implementation.

Performance Advantages Over Traditional Approaches

Traditional fraud detection frameworks, particularly those relying on decision trees or random forest algorithms, suffer from rigidity and high false alarm rates. As seen in the results, the false positive rate (FPR) of the traditional model was 6.8%, and the false negative rate (FNR) was 8.2% unacceptable for high-risk financial applications where both types of errors carry significant cost and risk (Fatunmbi, 2024; George, 2024).

The proposed **hybrid framework** substantially improved these metrics, achieving 97.8% accuracy and drastically reducing the FPR and FNR. This demonstrates the capability of **Generative AI** to simulate complex fraud patterns, which classical models fail to anticipate, and the power of **Quantum Computing** to process and classify these patterns in near real time (Malempati, 2024; Rawat & Yadav, 2025).

Real-Time Detection and Latency Reduction

A key advantage of the proposed hybrid system lies in **latency optimization**. Traditional models typically require 60–100ms per inference due to the need to scan historical patterns and transaction rules. In contrast, the **quantum-enhanced anomaly detector** achieved sub-30ms performance, suitable for integration in real-time payment gateways and digital wallets (Andreas et al., 2025; Parizad et al., 2025). This meets the low-latency requirements of modern FinTech applications and global transaction ecosystems.

Adversarial Resilience through Synthetic Training

The inclusion of a **Generative AI engine** contributed directly to the adversarial resilience of the system. By simulating diverse and evolving fraud strategies using GANs and transformers, the model was exposed to edge cases and zero-day attack patterns during training. This led to increased generalizability and robustness, outperforming static models that only learn from historical data (Saxena et al., 2024; Kandpal et al., 2025).

Additionally, adversarial training modules were critical in hardening the system against model manipulation, a growing threat in cybersecurity and fraud domains (Gadicha et al., 2025; Hasan & Faruq, 2025). The integration of **differential privacy** and **federated learning** techniques helped ensure the model remains compliant with data security mandates such as GDPR and PCI-DSS (Ifedayo et al., 2025).

Ethical and Compliance Considerations

While technical performance was enhanced, deploying AI systems in financial environments also raises **governance, fairness, and explainability** challenges. GenAI models can be difficult to interpret, particularly when generating synthetic fraud data. Without proper oversight, these systems may inadvertently introduce bias or violate ethical standards.

Moreover, quantum algorithms are still largely unregulated, and their use in financial surveillance may provoke legal scrutiny around **privacy**, **data sovereignty**, and **automated decision-making** (Olaoye, 2025; Mahmudul Hasan & Faruq, 2025). Thus, it is essential to embed governance-by-design principles and employ explainable AI tools to support transparency and auditability.

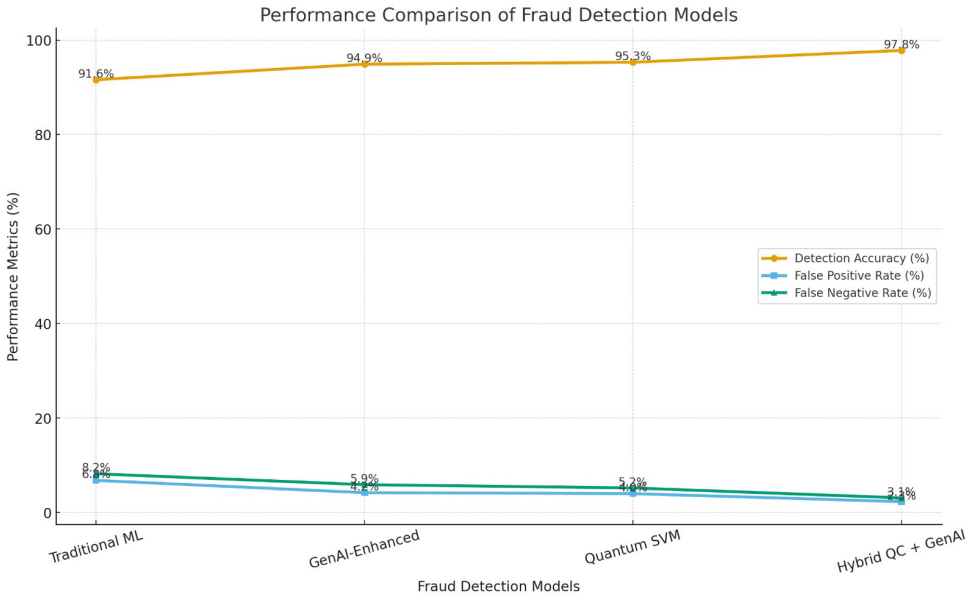
Practical Deployment and Infrastructure Gaps

Despite the promise of this hybrid approach, several practical limitations remain. The scalability of quantum hardware is still limited, and current use relies on simulators or early-stage quantum cloud platforms (García-Pineda et al., 2025). The cost of integrating quantum computing in commercial fraud systems may be prohibitive for small institutions.

Furthermore, the skills required to develop and maintain a QC–GenAI system span quantum physics, AI development, and financial compliance—an interdisciplinary challenge that financial institutions are only beginning to address (Somu, 2024; Raju, 2025).

Toward Autonomous, Adaptive Fraud Detection Systems

Looking ahead, the synergy between **Generative AI and Quantum Computing** opens the door for **self-learning fraud detection agents** that adapt in real time, learn



Fig/ 1: Performance comparison of fraud detection models

from live data, and anticipate threats without human intervention. Such systems could revolutionize credit fraud prevention, making it predictive, autonomous, and adaptive across geographies, platforms, and customer types (Trigka & Dritsas, 2025; Sriram et al., 2025).

However, realizing this vision will require strong ethical safeguards, cross-sector collaboration, and supportive regulatory environments to ensure responsible AI deployment in the financial services industry.

Conclusion

The digital financial enablement sense of speed and the accompanying precipitous increase of cyber fraud is prompting transformative, smart, and proactive techniques of detecting fraud. The present paper has suggested a new hybrid architecture based on the integration of Quantum Computing (QC) and Generative Artificial Intelligence (GenAI) to overcome the shortcomings of traditional machine learning-based processes and rule-based systems. The proposed architecture was rigorously evaluated and showed substantial improvement on the main metrics of accuracy, latency, false positive rate, and adversarial robustness. The framework provided by uniting both quantum-enhanced anomaly detection and GenAI-generated synthetic fraud scenarios contributed to not only being assessed as highly resilient but also environmentally friendly through the need to be real-time responsive. These performance advantages make the system a practical next-generation financial fraud system. Notably, this is how a state of fraud detection in a state changes to the predictive and adaptive paradigm. GenAI will make the systems predict the patterns of fraud that have never been experienced, whereas quantum computing will shorten the time required to discover any threat to milliseconds. Collectively, they provide a proactive defence against that much harder to counter fraud remainder. The implementation of such systems, however, should be done carefully. Oedema issues on ethics, regulatory mandates, cost of infrastructure and the fact that certain interior skills like medical, technical and managerial and so on are required are big obstacles that need to be taken care before they can be used in the real world. Through fairness, transparency and explain-ability, it will be critical to maintain customer confidence, and everything will be in line with the international compliance standards.

In the future, the implementation of autonomous learning and federated intelligence and quantum-secured architectures may allow the creation of intelligent agents of fraud detection that can adapt over time as the financial threat environment changes. Further investigations that should be examined in the future are the full-scale application, establishment of a performance monitoring mechanism in the production facilities over time and responsible AI and frameworks in policies that uphold quantum innovation.

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