INTERNATIONAL JOURNAL OF RESEARCH AND INNOVATION IN SOCIAL SCIENCE (IJRISS)
ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue VII July 2026

Artificial Intelligence in Financial Fraud Detection: Current Applications, Challenges, and Future Directions

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DOI: https://doi.org/10.47772/IJRISS.2026.100700636

Received: 26 July 2026; Accepted: 31 July 2026; Published: 08 August 2026

ABSTRACT

Financial fraud has emerged as one of the most significant threats to global economic stability, resulting in billions of dollars in annual losses for financial institutions, businesses, governments, and individual consumers. The rapid digitization of financial services, expansion of online banking, growth of electronic payment systems, and increasing sophistication of cybercriminal activities have rendered traditional fraud detection mechanisms insufficient. Artificial Intelligence (AI) has transformed financial fraud detection by enabling automated identification of suspicious transactions, real-time monitoring of financial activities, predictive analytics, and adaptive learning capabilities that continuously improve detection accuracy. This literature review examines the current applications of AI in financial fraud detection, including machine learning, deep learning, natural language processing, anomaly detection, and graph-based analytical approaches. The review further explores major challenges associated with AI deployment, such as data quality limitations, model interpretability, privacy concerns, adversarial attacks, regulatory compliance, and algorithmic bias. Additionally, emerging trends and future directions are discussed, including explainable AI, federated learning, blockchain integration, quantum-enhanced fraud analytics, and autonomous fraud prevention systems. The review highlights the transformative potential of AI while emphasizing the need for ethical, transparent, and secure implementation strategies to maximize effectiveness in combating increasingly sophisticated financial fraud schemes.

Keywords: Artificial Intelligence, Financial Fraud Detection, Machine Learning, Deep Learning, Cybersecurity, Financial Technology, Explainable AI, Fraud Analytics, Banking Security, Digital Finance

INTRODUCTION

The rapid advancement of digital technologies has fundamentally transformed the global financial ecosystem. Over the past two decades, financial institutions have increasingly embraced digital banking platforms, electronic payment systems, mobile financial services, online lending, peer-to-peer payment applications, cryptocurrency exchanges, and cloud-based financial infrastructures [1-3]. While these technological innovations have improved accessibility, efficiency, and convenience for consumers and businesses alike, they have simultaneously expanded the attack surface available to cybercriminals and financial fraudsters. As a result, financial fraud has evolved into a highly sophisticated and dynamic threat that poses significant economic, operational, and reputational risks to financial institutions worldwide.

Financial fraud refers to any intentional act of deception designed to obtain unauthorized financial gain [4]. Modern forms of financial fraud include credit card fraud, identity theft, account takeover attacks, insurance fraud, loan fraud, money laundering, phishing schemes, insider trading, tax evasion, and cryptocurrency-related fraud [5-8]. The growing complexity of these fraudulent activities has been driven by increased digitalization, cross-border financial transactions, anonymity provided by certain technologies, and the availability of advanced cybercrime tools [9]. According to global financial crime reports, financial institutions lose billions of dollars annually due to fraudulent activities, with indirect costs such as regulatory penalties, customer compensation, and reputational damage often exceeding direct monetary losses [10, 11]. Traditional fraud detection systems have historically relied on rule-based frameworks and manual auditing procedures [12, 13]. These systems operate by identifying predefined patterns of suspicious activity, such as unusually large transactions, multiple failed login attempts, or transactions originating from high-risk geographical locations. Although rule-based approaches remain useful in detecting well-established fraud patterns, they often struggle to adapt to rapidly evolving fraud tactics. Fraudsters continuously modify their techniques to evade detection, rendering static rules increasingly ineffective, and the growing volume of financial transactions generated daily by modern digital economies exceeds the analytical capacity of traditional monitoring systems.

Artificial Intelligence (AI) has emerged as one of the most promising solutions to address these challenges [14, 15]. AI encompasses a broad range of computational techniques that enable machines to mimic aspects of human intelligence, including learning, reasoning, prediction, and decision-making [16, 17]. Through the use of machine learning algorithms, deep neural networks, natural language processing systems, and advanced analytical models, AI-driven fraud detection systems can analyze vast amounts of financial data, identify subtle anomalies, recognize complex behavioral patterns, and continuously improve their performance through experience. Unlike conventional systems, AI-based approaches can adapt to emerging fraud strategies and provide real-time detection capabilities, significantly enhancing the effectiveness of fraud prevention efforts. The adoption of AI in fraud detection has accelerated considerably in recent years due to advancements in computational power, cloud computing infrastructure, big data analytics, and the increasing availability of large-scale financial datasets. Financial institutions, regulatory agencies, payment processors, insurance companies, and fintech organizations are investing heavily in AI-powered fraud management solutions to strengthen security, reduce operational costs, and improve customer trust. These investments reflect a broader recognition that traditional approaches alone are no longer sufficient to address the growing sophistication of financial crime.

Despite its transformative potential, the implementation of AI in fraud detection is not without challenges. Concerns surrounding data privacy, algorithmic transparency, model bias, regulatory compliance, and adversarial attacks continue to raise important questions regarding the responsible deployment of AI technologies in financial settings. Understanding both the opportunities and limitations of AI-based fraud detection systems is therefore essential for researchers, policymakers, financial institutions, and technology developers. This literature review critically examines the current state of artificial intelligence in financial fraud detection. Specifically, it explores major AI methodologies and their applications across various fraud domains, evaluates the benefits and limitations of existing approaches, discusses key implementation challenges, and identifies future research directions that may shape the next generation of intelligent fraud detection systems. Through this analysis, the review aims to provide a comprehensive understanding of how AI is transforming fraud detection and contributing to the security and resilience of the global financial system.

Evolution of Fraud Detection Technologies

The evolution of fraud detection technologies reflects the broader technological transformation of the financial sector itself. As financial systems have become increasingly digitized, fraud detection methodologies have evolved from simple manual inspections to highly sophisticated artificial intelligence-driven analytical frameworks [18, 19], understanding this progression is critical for appreciating the significance of current AI applications and identifying opportunities for future innovation. In the early stages of modern banking, fraud detection was primarily conducted through manual auditing and human oversight [20, 21]. Financial institutions relied heavily on accountants, auditors, compliance officers, and investigators to review financial records, identify discrepancies, and investigate suspicious activities [22]. While effective for relatively small transaction volumes, these approaches were labor-intensive, time-consuming, and vulnerable to human error. As financial systems expanded and transaction volumes increased, manual methods became increasingly impractical and insufficient for detecting fraud in a timely manner. The first major technological advancement in fraud detection emerged through rule-based expert systems [23]. These systems utilized predefined rules developed by fraud analysts and domain experts to identify suspicious transactions. For example, transactions exceeding certain monetary thresholds, unusual spending behaviors, multiple withdrawals within a short period, or transactions occurring from unfamiliar locations would trigger alerts for further investigation. Rule-based systems represented a significant improvement over manual monitoring by automating the identification of known fraud patterns.

Despite their widespread adoption, rule-based systems exhibited several important limitations, their effectiveness depended entirely on the quality and completeness of predefined rules, making them inherently reactive rather than proactive [24, 25]. New fraud schemes could remain undetected until experts identified the pattern and updated the system accordingly. Furthermore, maintaining large rule databases became increasingly complex as fraud scenarios diversified. These systems also generated high false-positive rates, leading to operational inefficiencies and customer dissatisfaction. The emergence of data mining techniques during the late 1990s and early 2000s marked a significant turning point in fraud detection research [26-28]. Data mining enabled financial institutions to extract hidden patterns and relationships from large datasets without relying exclusively on manually defined rules [29]. Statistical techniques such as regression analysis, clustering, decision trees, and association rule mining were increasingly employed to identify potentially fraudulent behaviors. These approaches facilitated more data-driven fraud detection strategies and laid the foundation for subsequent machine learning applications.

The development of deep learning technologies represented another major milestone in the evolution of fraud detection systems [30]. Deep neural networks, inspired by the structure and function of biological neural systems, possess the ability to automatically learn hierarchical representations of data [31]. These models can capture highly complex nonlinear relationships and identify subtle fraud indicators that may be overlooked by traditional machine learning approaches. Applications of deep learning in fraud detection include credit card fraud identification, anti-money laundering systems, insurance fraud detection, and transaction monitoring platforms [32, 33]. Recent years have witnessed the emergence of advanced AI methodologies that extend beyond traditional machine learning and deep learning. Graph-based analytics, for example, have become increasingly important in detecting organized financial crime and money laundering networks [34-36]. By analyzing relationships among accounts, individuals, devices, and transactions, graph-based approaches can uncover hidden connections and identify fraudulent networks that would be difficult to detect through transaction-level analysis alone. Similarly, natural language processing technologies have enabled the analysis of unstructured data sources such as emails, financial reports, customer communications, and social media content to identify potential indicators of fraudulent behavior, and the integration of real-time analytics has further transformed fraud detection capabilities [37-39].

Modern AI-powered systems can evaluate thousands of transactions per second, generating instantaneous risk assessments and enabling immediate intervention when suspicious activities are detected. This shift from retrospective investigation to proactive prevention has significantly reduced fraud-related losses and improved customer protection. Today, fraud detection technologies continue to evolve through the incorporation of explainable AI, federated learning, blockchain technologies, and quantum computing research. These innovations seek to address current limitations related to transparency, privacy, scalability, and computational efficiency while enhancing the overall effectiveness of fraud detection systems. The ongoing evolution of fraud detection technologies demonstrates a clear trajectory toward increasingly intelligent, autonomous, and adaptive systems capable of responding to the ever-changing landscape of financial crime.

Current Applications of Artificial Intelligence in Financial Fraud Detection

Artificial Intelligence has revolutionized the financial industry's approach to fraud detection by enabling institutions to move from reactive investigations toward proactive prevention. Modern financial systems generate enormous volumes of structured and unstructured data every second through digital payments, online banking, credit card transactions, mobile applications, cryptocurrency exchanges, insurance claims, and investment platforms. Traditional fraud detection methods are often incapable of processing these large-scale datasets efficiently, creating opportunities for AI-driven systems to fill critical gaps in financial security frameworks. AI-based fraud detection systems operate by identifying abnormal patterns, behavioral deviations, hidden relationships, and emerging threats within financial data. These systems continuously learn from historical transactions and adapt to new fraud tactics, making them particularly effective against rapidly evolving cybercrime strategies.

Machine Learning-Based Fraud Detection

Machine learning remains the most extensively adopted AI technology in financial fraud detection. Machine learning algorithms identify complex relationships within transaction datasets and generate predictive models capable of distinguishing legitimate transactions from fraudulent activities [40, 41]. Supervised learning models are commonly trained using historical datasets containing labeled examples of both fraudulent and nonfraudulent transactions [42]. Algorithms such as Logistic Regression, Decision Trees, Random Forests, Support Vector Machines (SVM), and Extreme Gradient Boosting (XGBoost) have demonstrated remarkable effectiveness in fraud classification tasks [43]. These models evaluate multiple transaction variables simultaneously, including transaction amount, frequency, location, device characteristics, account history, and customer behavior patterns. Random Forest and XGBoost algorithms have gained particular popularity due to their ability to handle high-dimensional datasets while maintaining strong predictive performance. Studies consistently demonstrate that ensemble learning methods outperform traditional statistical approaches in detecting subtle fraud patterns while reducing false-positive rates [44-48].

Unsupervised learning approaches have become increasingly valuable because fraud datasets are inherently imbalanced, with fraudulent transactions representing only a small fraction of total financial activities [49, 50]. Algorithms such as K-Means Clustering, Isolation Forests, and Autoencoders identify anomalous behaviors without requiring labeled training data. These methods are particularly useful for detecting previously unseen fraud schemes that may not exist in historical datasets. The adoption of machine learning has enabled financial institutions to improve fraud detection accuracy while significantly reducing investigation costs. Many global banks now employ machine learning systems capable of analyzing millions of transactions daily with minimal human intervention.

Deep Learning Applications

Deep learning represents an advanced subset of machine learning that utilizes multilayered neural networks to model highly complex data relationships. Deep learning has become increasingly important in fraud detection because modern financial fraud often involves intricate patterns that cannot be effectively captured through conventional analytical techniques [51]. Artificial Neural Networks (ANNs) are widely used to analyze customer transaction behaviors and identify subtle indicators of fraud [52]. These systems learn hierarchical feature representations automatically, eliminating the need for extensive manual feature engineering. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are particularly effective for analyzing sequential financial data [53]. Fraudulent activities frequently involve patterns that unfold over time rather than isolated transactions. LSTM models can recognize temporal dependencies within transaction histories, enabling early detection of suspicious behavioral changes [54]. Convolutional Neural Networks (CNNs), originally developed for image recognition, have also been adapted for financial applications [55]. Researchers have demonstrated their effectiveness in identifying complex transaction patterns and detecting anomalies within multidimensional financial datasets [56, 57]. These models can analyze textual communications, financial reports, customer interactions, and regulatory documents to identify fraud-related indicators that may otherwise remain undetected.

Natural Language Processing in Fraud Detection

Natural Language Processing (NLP) enables computers to understand, interpret, and analyze human language. In financial fraud detection, NLP provides powerful capabilities for extracting insights from unstructured textual data [58]. Financial institutions increasingly utilize NLP systems to analyze customer emails, chat conversations, transaction descriptions, insurance claims narratives, loan applications, and regulatory filings [59]. By identifying suspicious language patterns, inconsistencies, or deceptive communication strategies, NLP systems can help detect fraud at early stages. Phishing attacks remain among the most common forms of financial fraud. NLP-based fraud detection tools can analyze email content, identify malicious intent, and classify messages according to fraud risk levels [60]. Sentiment analysis and semantic understanding further improve the identification of deceptive communication tactics used by cybercriminals. Modern language models can recognize contextual relationships, detect subtle linguistic cues, and identify fraudulent narratives with greater accuracy than previous generations of NLP systems.

Graph Analytics and Network-Based Fraud Detection

Many financial crimes involve complex networks of interconnected individuals, organizations, devices, and financial accounts. Traditional transaction-level analysis often fails to identify these broader relationships. Graph analytics addresses this challenge by representing financial ecosystems as interconnected networks [61]. Nodes represent entities such as customers, accounts, devices, or organizations, while edges represent relationships or transactions between them. Graph Neural Networks (GNNs) have emerged as powerful tools for detecting organized fraud schemes [62]. Applications include anti-money laundering investigations, synthetic identity fraud detection, terrorist financing surveillance, and cryptocurrency fraud monitoring. By examining network structures and relationship patterns, graph-based systems can uncover hidden fraud rings and coordinated criminal activities that may remain invisible through conventional analytical approaches.

Real-Time Fraud Detection Systems

One of the most transformative contributions of AI is the ability to detect fraud in real time. Modern financial transactions occur within milliseconds, necessitating equally rapid fraud detection mechanisms as show in Table 1 below. AI-powered real-time systems continuously monitor transaction streams and assign risk scores based on dynamic behavioral models. High-risk transactions can be flagged, delayed, or blocked before completion. Real-time fraud detection significantly reduces financial losses by preventing fraudulent transactions rather than merely identifying them after the fact [63, 64]. Furthermore, these systems improve customer trust by minimizing the impact of financial crime on legitimate users.

Table 1: Major AI Technologies Used in Financial Fraud Detection

AI Technology	Primary Function	Common Applications
Machine Learning	Pattern recognition	Credit card fraud detection
Deep Learning	Complex nonlinear modeling	Transaction monitoring
NLP	Text analysis	Phishing and document fraud
Graph Analytics	Relationship analysis	Money laundering detection
Reinforcement Learning	Adaptive decision-making	Dynamic fraud prevention
Explainable AI	Model interpretation	Regulatory compliance

Benefits and Performance of AI-Based Fraud Detection Systems

The adoption of AI technologies has substantially improved the effectiveness and efficiency of fraud detection systems across the financial sector. One of the most significant benefits is enhanced detection accuracy. Traditional rule-based systems often generate large numbers of false positives because they rely on simplistic decision criteria. AI systems, by contrast, analyze multiple variables simultaneously and identify complex relationships that improve classification performance. Another major advantage is scalability. Financial institutions process millions of transactions daily, making manual review impossible. AI systems can evaluate massive transaction volumes in real time without compromising performance. AI systems also demonstrate remarkable adaptability. Fraudsters continuously develop new techniques to circumvent existing security measures. Machine learning models can retrain on newly available data, allowing them to adapt to evolving fraud patterns more effectively than static rule-based approaches. Cost reduction represents another important benefit. Automated fraud detection minimizes the need for extensive manual investigations, reducing operational expenses while improving productivity. Furthermore, AI contributes to improved customer experiences by reducing unnecessary transaction declines and minimizing disruptions caused by false fraud alerts. This balance between security and convenience is critical for maintaining customer satisfaction and trust.

Challenges, Ethical Concerns, and Regulatory Issues

Despite substantial advancements, numerous challenges continue to limit the effectiveness and adoption of AI-based fraud detection systems as shown in Table 2 below. The performance of AI systems depends heavily on the quality of training data [65]. Incomplete, inconsistent, or inaccurate datasets can significantly reduce model effectiveness. Financial fraud datasets are often highly imbalanced because fraudulent transactions constitute only a small percentage of total transactions [66, 67]. This imbalance can cause models to become biased toward predicting legitimate transactions while overlooking rare fraud cases. Many advanced AI models, particularly deep neural networks, operate as "black boxes." While they may achieve high predictive accuracy, understanding the rationale behind their decisions can be difficult. Regulators increasingly require financial institutions to explain automated decisions affecting customers, and the lack of transparency may undermine trust and complicate compliance efforts. Fraud detection systems frequently process sensitive personal information, including financial records, biometric data, and behavioral profiles [68]. Fraudsters increasingly target AI systems themselves, and the adversarial attacks may involve manipulating input data to evade detection or poisoning training datasets to degrade model performance. Such attacks represent a growing cybersecurity concern that requires robust defensive mechanisms and continuous monitoring. AI models trained on biased datasets may inadvertently discriminate against specific demographic groups, while this can lead to unfair treatment, legal challenges, reputational damage, and regulatory scrutiny.

Table 2: Major Challenges in AI-Based Fraud Detection

Challenge	Description	Potential Impact
Data Imbalance	Few fraud cases relative to legitimate transactions	Reduced detection accuracy
Privacy Concerns	Sensitive customer information	Regulatory violations
Explainability	Black-box decision making	Reduced trust
Adversarial Attacks	AI manipulation by fraudsters	Security vulnerabilities
Bias	Unequal treatment of users	Ethical and legal issues

Future Directions

The future of AI-driven fraud detection will be shaped by a convergence of emerging technologies that address current limitations while significantly enhancing analytical capabilities, operational efficiency, and security resilience. As financial fraud becomes increasingly sophisticated, future fraud detection systems will need to move beyond traditional predictive models toward intelligent, transparent, collaborative, and autonomous security ecosystems. One of the most important developments is the growing adoption of Explainable Artificial Intelligence (XAI) [69]. Although machine learning and deep learning models have demonstrated remarkable performance in fraud detection, many operate as "black boxes," making it difficult for regulators, auditors, and financial institutions to understand how decisions are reached. Future fraud detection platforms are expected to incorporate explainability mechanisms that provide clear and interpretable justifications for fraud alerts and risk assessments. Techniques such as SHapley Additive exPlanations (SHAP), Local Interpretable Model-Agnostic Explanations (LIME), counterfactual explanations, and attention visualization frameworks will likely become integral components of AI architectures. The increased transparency provided by these approaches will improve regulatory compliance, strengthen customer trust, facilitate auditing processes, and reduce concerns regarding algorithmic bias.

Another promising direction is the expansion of federated learning and privacy-preserving artificial intelligence [70]. Financial institutions often possess valuable fraud-related data, but legal, ethical, and privacy constraints frequently limit direct data sharing. Federated learning enables multiple organizations to collaboratively train machine learning models without transferring sensitive customer information outside their local environments. This decentralized approach allows institutions to benefit from collective fraud intelligence while maintaining data confidentiality and regulatory compliance. As cyber threats continue to evolve globally, federated learning may support the development of more robust and adaptive fraud detection systems capable of identifying emerging fraud patterns across multiple institutions and geographic regions.

The integration of blockchain technology with artificial intelligence is also expected to play a significant role in future fraud prevention strategies. Blockchain provides immutable, transparent, and tamper-resistant transaction records that can serve as highly reliable data sources for AI algorithms. By combining blockchain's distributed ledger capabilities with AI-driven analytics, financial institutions can improve transaction traceability, strengthen anti-money laundering (AML) programs, reduce opportunities for data manipulation, and enhance overall financial transparency. Smart contracts integrated with AI systems may further automate fraud prevention processes by enforcing predefined security rules and triggering real-time responses when suspicious activities are detected.

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue VII July 2026

Although still in the early stages of development, quantum computing represents another transformative technology with the potential to revolutionize financial fraud analytics. Traditional computing systems face limitations when processing extremely large datasets and solving highly complex optimization problems. Quantum computing may dramatically accelerate data analysis, pattern recognition, network analysis, and anomaly detection tasks that are currently computationally intensive. Future quantum-enhanced machine learning algorithms could improve the speed and accuracy of fraud detection systems, enabling financial institutions to identify sophisticated fraud schemes that would otherwise remain undetected using conventional technologies. While practical implementation may still be years away, ongoing advancements suggest that quantum computing could become a major component of next-generation fraud intelligence platforms.

Perhaps the most transformative future development is the emergence of autonomous fraud prevention systems. Current AI applications primarily focus on detecting suspicious activities and alerting human analysts for further investigation. Future systems are expected to evolve beyond detection toward proactive and autonomous prevention. These systems will not only identify fraudulent behavior but also automatically implement appropriate countermeasures in real time. Examples include adaptive authentication protocols, intelligent transaction blocking, dynamic risk scoring, self-adjusting security policies, and self-learning defense mechanisms that continuously improve through experience. Such autonomous systems may significantly reduce response times, minimize financial losses, and enhance organizational resilience against rapidly evolving fraud threats. These technological advancements indicate a future in which fraud detection systems become increasingly transparent, collaborative, intelligent, and autonomous. The integration of explainable AI, federated learning, blockchain technologies, quantum computing, and autonomous prevention frameworks has the potential to create highly adaptive security infrastructures capable of responding effectively to the growing complexity of financial crime.

CONCLUSION

Artificial Intelligence has fundamentally transformed the landscape of financial fraud detection by enabling institutions to identify, analyze, and prevent fraudulent activities with unprecedented speed, accuracy, and scalability. Through the application of machine learning, deep learning, natural language processing, graph analytics, behavioral modeling, and real-time monitoring systems, financial organizations can now detect complex fraud patterns that were previously difficult or impossible to identify using traditional rule-based approaches. These technological advancements have significantly strengthened financial security, improved customer protection, reduced operational losses, and enhanced trust within digital financial ecosystems. Despite these substantial benefits, the successful implementation of AI-driven fraud detection systems remains dependent on overcoming several critical challenges. Issues related to data quality, algorithmic bias, privacy protection, model transparency, cybersecurity vulnerabilities, and regulatory compliance continue to influence the effectiveness and acceptance of AI technologies. Furthermore, fraudsters are increasingly leveraging advanced digital tools, including artificial intelligence itself, to develop more sophisticated attack strategies. Consequently, fraud detection systems must remain dynamic, continuously updated, and capable of adapting to evolving threat environments.

From a policy perspective, governments and regulatory authorities must establish comprehensive governance frameworks that encourage innovation while ensuring accountability, fairness, transparency, and consumer protection. Regulatory guidelines should promote responsible AI adoption, standardize explainability requirements, strengthen data protection measures, and support ethical deployment practices across the financial sector. International cooperation among regulators, financial institutions, technology providers, and academic researchers will also be essential because financial fraud increasingly operates across national boundaries and digital platforms. Looking ahead, future research should prioritize the development of explainable and trustworthy AI systems, privacy-preserving machine learning frameworks, blockchain-enabled fraud monitoring architectures, quantum-enhanced analytical models, and autonomous fraud prevention technologies. Research should also focus on improving fairness, reducing algorithmic bias, enhancing cross-institutional collaboration, and strengthening resilience against emerging cyber threats.

In conclusion, the future effectiveness of financial fraud detection will depend not only on advances in artificial intelligence but also on the ability of institutions to integrate these technologies within robust governance, ethical, and regulatory frameworks. Financial organizations that successfully combine technological innovation with transparency, accountability, and strategic risk management will be better positioned to combat increasingly sophisticated fraud schemes. Ultimately, the continued evolution of AI-powered fraud detection systems offers a pathway toward more secure, resilient, trustworthy, and sustainable global financial ecosystems.

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