International Journal of Science and Research Archive
eISSN: 2582-8185
Cross Ref DOI: 10.30574/ijsra
Journal homepage: https://ijsra.net/

(REVIEW ARTICLE)

Check for updates

Strengthening financial system stability through Artificial Intelligence Enabled Risk Surveillance, Crisis Detection and Strategic Resilience

Elizabeth Ope [1, *], Yejide R. Alli [2], Ifeoluwa A. Ojo [3], Oyindamola Adejumobi [4], Aniedi Ojo [5] and Victoria Enoc-Ahiamadu [6]

[1] Department of Economics, Andrew Young School of Policy Studies, Georgia State University, United States.
[2] University of North Carolina Chapel Hill, Kenan Flagler Business School, NC, USA.
[3] Haas School of Business, University of California, Berkeley, Berkeley, California, USA.
[4] Robert McKinney School of Law, Indiana University, Indianapolis, Indiana, USA.
[5] The Faqua School of Business, Duke University, Durham, North Carolina, USA.
[6] Harvard Business School, Boston, Massachusetts, USA.

International Journal of Science and Research Archive, 2026, 20(02), 432–439

Publication history: Received on 28 June 2026; revised on 09 August 2026; accepted on 11 August 2026

Article DOI: https://doi.org/10.30574/ijsra.2026.20.2.1594

Abstract

The world financial environment is characterised by increasing interdependence, rapid technological change and cyclic economic crises such that current and legacy EWS is no longer useful in regard to macroeconomic governance. Conventional models, based on lagging indicators and historical data, do not take into account contagion non-linearities, velocity and systemic shocks in the digital world, such as algorithmic "flash" crashes or "bank" runs. The paper suggests the use of AI to overcome these issues, through real-time monitoring and early warning of risks. The suggested Multi-layered structure to combine Big Data, Machine Learning and Artificial Intelligence in the macroeconomic direction is based on the Financial Instability Hypothesis (FIH) of Minsky and the theory of Complex Adaptive Systems (CAS). The architecture comprises data ingestion, core analytics (unsupervised anomaly detection, network contagion mapping and supervised crisis forecasting) and decisions support operational dashboards. Moreover, it discusses a dynamic stress test using Generative Adversarial Networks (GANs), answers key questions in the context of Explainable AI (XAI) and data privacy, and offers a recommended course of action in implementing and standardised RegTech/SupTech systems to transition regulatory control to an active and proactive science.

Keywords: Artificial Intelligence (AI); Complex Adaptive Systems (CAS); Crisis Detection; Early Warning Systems (EWS); Financial System Stability; Machine Learning (ML); Macroprudential Governance; Regtech and Suptech; Risk Surveillance.

1. Introduction

The global financial landscape is changing drastically, with its markets becoming more and more interconnected, new technologies being developed at a rapid pace, and more and more economic shocks occurring. Traditional macroeconomic governance is confronted with new challenges and conditions, which call for new methods and procedures, as financial systems become more complex and systemic risks amplify and become more unstable, uncertain and unpredictable than ever before [1]. Policymakers and financial institutions have to navigate in a financial system that faces new risks, challenges and conditions, and which poses an unprecedented need for new methods and procedures for maintaining financial stability and for fulfilling sustainability and growth aspects[2].

* Corresponding author: Elizabeth Ope.

These models have been used traditionally, doing a 'post-mortem' on the economy, looking at lagging indicators and assuming that financial health is best measured by looking at historical data, but in less stable economic times, those models leave the regulators and institutions 'blind' to emerging, non-linear threats [3]. These legacy models are not able to reflect complex contagion scenarios, sudden market turns, and tail events, and therefore new forward-looking and real-time risk assessment tools able to adjust to fast-paced financial markets are essential [4].

Compounding these structural challenges are the unprecedented velocity and complexity of modern systemic shocks, including algorithmic flash crashes, instantaneous cross-border contagion, and digital bank runs executed at unprecedented speeds, that are not yet observed by conventional early warning systems (EWS) which are mostly based on low frequency reporting metrics and linear assumptions that lack the granularity to capture the cascading nature of contemporary financial crises [5] This latent period between the emergence of a systemic vulnerability and the recognition of this vulnerability by regulatory authorities is conducive to broad-based economic contagion before a mitigating response can be put in place [6]

The primary goal of this paper is to imagine a sophisticated framework, powered by AI, to monitor and proactively detect risk and crisis in real-time. The study offers central banks and financial regulators the critical architectural, operational and substantive policy design perspectives to make the leap from macroprudential policy theory to practice in the digital sphere. Last, an extensive empirical framework is used to evaluate the use of Big Data, Machine Learning (ML) and Artificial Intelligence (AI) for macroeconomic governance. This study is pertinent because it may transform the re-active and re-trospective regulatory oversight to an agile and predictive science. The study empowers policymakers with state-of-the-art surveillance tools that are relevant to the difficult but evolving digital economic age and key to global financial stability.

2. Literature Review & Theoretical Framework

Financial Early Warning Systems (EWS) have undergone a paradigm change from early qualitative econometric models to current high-frequency quantitative models [7] EWS traditionally placed much weight on low frequency macroeconomic aggregates and expert judgment which tended to come with significant detection lags. Today, a real-time data feed provides an up-to-the-minute snapshot of the market, including current price changes, liquidity and detailed transactions – thus providing a more specific and nuanced view of the financial landscape [8].

This sort of surveillance over the present day must be placed within a theoretical framework, in this case the Financial Instability Hypothesis of Minsky [9]. The relevance of Minsky's statement is great for regulators today, since it is the awareness of the risk that can only be explained as endogenously generated by the financial system that is a key component to explaining the sudden turn around in seemingly healthy markets towards systemic meltdowns, especially when they are based on debt financing.

Alongside the thoughts of Minsky, the Complex Adaptive Systems (CAS) theory can provide an effective way of thinking about the modern financial markets as highly dynamic networks of many interacting agents with emergent behaviour - a myriad of interactions become complex giving rise to unpredictable global repercussions through novel feedback loops and channels of contagion that develop at a very fast pace [10]. CAS theory may provide a little further understanding about why a reductionist approach is no longer adequate and systemic risk may manifest in more than just individual institutional breakdowns [11].

Such dynamic and complex environments require more complex computational solutions, and AI and ML become particularly relevant in the modern financial environment. Supervised learning algorithms can be tuned with crisis patterns and can be used to identify known vulnerabilities, whereas unsupervised learning will work with no human intervention to identify new anomalies and structural breaks as they occur within the real-time data stream [12]. Moreover, with Natural Language Processing (NLP) at the forefront of RegTech, unstructured textual data, including central bank statements, news feeds and regulatory disclosures, can be analyzed to identify sentiment changes in the market and to optimize compliance processes [13].

3. Conceptual Framework: AI-Enabled Risk Surveillance Architecture

In order to create an effective real-time risk surveillance system it is essential to have a comprehensive high-level architecture overview that is based on four essential tiers [15]. The data ingestion layer is continually collecting and ingesting high velocity streams of data that are supplied to a scalable-processing engine which can process very large quantities of data [16]. The data is cleaned, normalized and processed directly into advanced analytical models for deep pattern recognition, leading to an intuitive decision-support dashboard for giving regulators actionable, real-time visual insights.

A single ingestion plan is crucial to power this multi-layered architecture and to ensure that the variety of data sources across the modern financial landscape are harmonized [17]. Structured data (live market feeds, institutional balance sheets and interbank lending rates) serves as quantitative baseline for the daily monitoring of liquidity and leverage. Meanwhile, the most relevant and important changes in market sentiment (qualitative, systemic pressure) can be captured by looking at unstructured data elements, such as automated parsing of news feeds, and central bank transcript and social media sentiment [18].

Figure 1 AI-Enabled Risk Surveillance Architecture [14].

At the core of the system is the so-called 'macroprudential anomaly detection module' (modular component A), which implements unsupervised clustering algorithms to detect anomalies in the market automatically, without requiring the module to be retrained with historical labels for anomalies. In addition to this, Module B conducts advanced contagion and graph analysis of networks to demonstrate complex systemic relationships between institutions [19]. This module can generate a financial system graph of a network of nodes to show how small shocks can quickly propagate through the financial system and potentially threaten the overall stability of the entire network [38].

Finally, Module C completes the main analytical tool kit with the ability to forecast future crises with robust supervised classification techniques [20]. This module uses historical data of crisis indicators and validated financial stress scenarios to estimate the exact likelihood that a crisis is imminent before it manifests itself in the market. All of these analytical modules are built to fit in a single platform to turn raw and heterogeneous data feeds into a modern, proactive and intelligent defense for macroeconomic governance.

4. Comparative Analysis: Traditional vs. AI-Enabled Systems

Figure 2 Traditional vs. AI-Enabled Systems [21].

The difference between the traditional risk management processes and AI-powered surveillance systems is obvious when considering lags, dimensionality in data, and adaptability. Legacy models also have very high delays in the reporting of results, due to the use of infrequent and backward-looking indicator data, while modern machine learning architectures provide real-time results on streaming data with significantly lower delay [22]. Moreover, AI systems can easily handle large amounts of multi-dimensional data, such as both structured financial data indicators and unstructured textual sentiments, which is a challenge for traditional models due to their low-dimensional linear structures. Finally, AI models are dynamically adjustable and can continuously adjust to the various patterns visible in the marketplace, producing robust predictive capabilities throughout unusual periods of monetary volatility where traditional models are stationary and would require manual recalibration in case of a market structure change [23].

Table 1 Traditional vs. AI-Enabled Systems

Feature	Traditional Risk Surveillance	AI-Enabled Risk Surveillance
Data Processing	Batch processing, primarily structured metrics	Real-time streaming, multi-modal (structured & unstructured)
Detection Speed	Retrospective / Lagged (Monthly/Quarterly)	Real-time / Predictive (High-frequency)
Systemic Complexity	Assumes linear relationships and equilibrium	Captures non-linear dependencies and contagion loops
Adaptability	Rigid, requires manual recalibration	Dynamic, continuously learning via adaptive algorithms

Source: [24].

5. Crisis Detection and Macroprudential Intervention Mechanisms

Real-time stress testing challenges the concept of periodic stress testing, which is the traditional way of performing financial oversight, by leveraging dynamic scenario generation through Generative Adversarial Networks (GANs) [25]. GANs can generate new, very complex, unprecedented shocks and scenarios, out of the box, without relying on historical events or predefined scenarios which otherwise would be the ones that would emerge from legacy stress tests. Such capacity enables regulators and central banks to conduct simulations of never-before-seen tail risk events and the resulting bank-institutions' exposure to vulnerabilities they have never encountered [26].

Dynamic stress simulations are complemented by automated triggering, which enables in real time and probabilistic way the constitution of proactive regulatory structures with defined stress thresholds where action can be taken [27]. These smart triggers can automatically demand capital buffer adjustment or injection of specific liquidity, without people having to bother with committees or cumbersome quarterly reporting cycles, when issues of systemic risk exceed a defined threshold of safety. Through this algorithmic automation, the need for critical human response latency is removed, so stabilizing measures are taken when vulnerabilities start to form [28].

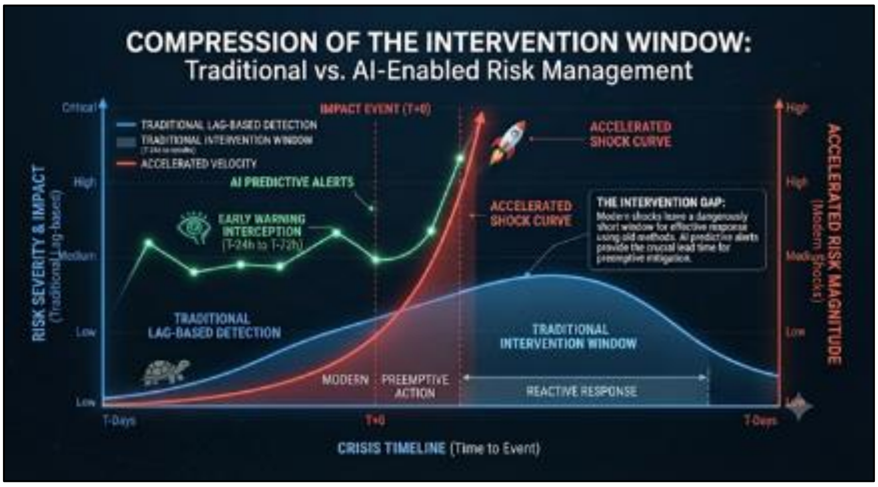

Figure 3 Stylized Risk Trajectory Curve [30].

Excellent dashboard interfaces reflect the emphasis placed on the question of how to offer policy makers actionable information on systemic weaknesses in the financial network. These tools, which are helpful for decision making and visualization, enable regulators to quickly visualize the multi-dimensional data, the network contagion graph and the output of the real time stress test [29]. These visualizations are interactive, making them easier to digest and understand than hard-to-navigate data, and helping the decision-makers of today's world to execute appropriate, effective actions in time, and in the right location, before a localized problem increases to become a systemic crisis.

6. Challenges, Risks, and Ethical Considerations

When using automated surveillance in high-stakes regulatory decisions, model risk and the need for Explainable AI (XAI) are key challenges. A key challenge with advanced machine learning models is the lack of transparency in the "black box" model that often prevents understanding why a model makes a particular risk prediction or generates an anomaly alert [31]. To the central banks and financial authorities, the binding regulatory action based on the opaque results of the computations is legally and ethically unsound and requires to be supported by robust XAI methodologies to make complex decisions by algorithms transparent, auditable, and justifiable to institutional stakeholders.

At the same time, macroprudential architecture for AI involves huge challenges in terms of data privacy, security, and cross-border information sharing [32]. Regulatory authorities have to continuously monitor complex international systemic flows while at the same time adhering to strict data protection legislation, and ensuring that no proprietary institutional data is compromised. Low-cost, secure, federated learning environments and privacy-preserving cryptographic protocols enable central banks to share the collective wisdom of the system across borders while at the same time keeping all (sensitive) commercial and transactional information completely from being ‘exposed' to unauthorised users [33].

Lastly, governance mechanisms are constantly under attack, whether through adversarial attacks or through algorithmic weaknesses. In the latter case, sophisticated actors could attempt to poison the data or intentionally manipulate the market conditions of what feeds into the AI models, make subtle changes to live data streams that may not be picked up by regulators - thereby evading regulation or creating false alarms [34]. To build resilience to such manipulation, it is necessary to conduct regular ‘audits’ to test and hone models, carry out adversarial training and establish strict validation alerts, ensuring that macroeconomic governance tools remain untampered and reliable in adverse scenarios [39].

7. Policy Recommendations and Future Research Directions

A rational and phased roadmap that paves the way for new and powerful units of AI and old legacy infrastructure, with a special emphasis on ‘modular analytics’ can be used one at a time to build a successful central bank or regulatory modernization for macro-economic governance, such as automated anomaly detection or natural language processing pipelines as supplemental layers on top of the old data warehouses without disturbing the institutional flows [35]. It is a practical solution to be able to make the regulatory community be capable of certifying algorithmic results, develop trust in the use of machine learning and expand the in-house technological capacity without replacing the current supervisory tasks [36].

In tandem with this architectural change, the need to standardise Regulatory Technology (RegTech) and Supervisory Technology (SupTech) frameworks, across the financial ecosystem, becomes relevant. RegTech compliance habits and working SupTech analytical centers can significantly cut down on administrative burden, increase data granularity, and create an ever-living and automatic wall of compliance that may assist in keeping the global financial system afloat in a fast-digitizing world [37].

8. Conclusion

The alignment of results is undeniable and speaks of a reality: the financial governance of today's times is at a point where digital transformation is no longer an optional choice, but rather a real need. The classical mode of regulation that is based on a slow and thinly sliced data reporting and negative attitude towards the data quality is per se insufficient in our increasingly connected and connected world. Based on the facts raised it became evident that the financial stability of the present time could be saved only through an active intelligent system that would be able to monitor and supervise in real-time and continuously.

The capabilities of the synergies between the Big Data, ML and AI will change the capabilities of the Central Banks as well as the Regulators. The powerful sets of analytic tools, unsupervised anomaly detection to networking contagion mapping up to even generative stress-testing can then be exploited. In addition, automated trigger mechanisms and easy to use decision support dashboards reduce man-made delays in responding to information, long since known as a fundamental factor in the origin and intensification of financial crises, and close the often-vast gap between sophisticated computational analyses and timely policy actions.

Lastly, the international regulators' key to this digital transformation is being open to it in a targeted and strategic manner. A step-by-step integration strategy is required to get to the challenges of explainability, data privacy and adversarial risk to bridge the mighty SupTech opportunities with the existing technology environment in institutions. By harmonising regulatory technology strategies and facilitating broad and deep cross-border data flows, central banks can build a strong and future-looking regulatory technology (Regtech) infrastructure to provide the digital economy with systemic stability.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

References

[1] Iddrisu K, Abor JY, Issah O, Gyebi FO. Monetary policy and inclusive growth in the era of economic uncertainty: navigating challenges and opportunities. Strategic approaches to banking business and sustainable development goals. 2025 Feb 13:263-83.

[2] Sutton CV. Navigating financial turbulence with confidence: preparing for future market challenges, crashes & crises. NuovoNova Ltd.; 2025 May 28.

[3] Rajeswaran N. Enhancing Financial Crisis Prediction with AI: Leveraging Historical Data and Machine Learning for Systemic Risk Management. Advances in Consumer Research. 2025 Mar 1;2(2).

[4] Odunaike A. Integrating real-time financial data streams to enhance dynamic risk modeling and portfolio decision accuracy. Int J Comput Appl Technol Res. 2025;14(08):1-6.

[5] Youvan DC. Emergent Phenomena in Modern Financial Systems: Unanticipated Risks and Their Mitigation. Journal of Financial Risk Management. 2024 Aug 8;13(1):89-102.

[6] Ahmadian M. Integrated central bank supervision in Islamic banking: necessities, challenges and solutions. Journal of Islamic Accounting and Business Research. 2026 May 15:1-6.

[7] Namaki A, Eyvazloo R, Ramtinnia S. A systematic review of early warning systems in finance. arXiv preprint arXiv:2310.00490. 2023 Sep 30.

[8] Knell M. Schumpeter, Minsky and the financial instability hypothesis. Journal of Evolutionary Economics. 2015 Jan;25(1):293-310.

[9] Booth A. Automated algorithmic trading: Machine learning and agent-based modelling in complex adaptive financial markets [doctoral dissertation]. University of Southampton; [year unknown].

[10] Cavallo A, Ireland V. Preparing for complex interdependent risks: a system of systems approach to building disaster resilience. International Journal of Disaster Risk Reduction. 2014 Sep 1;9:181-93.

[11] Duane J, Morgan A, Carter E. A review of financial data analysis techniques for unstructured data in the deep learning era: Methods, challenges, and applications. OSF Preprints. 2025 Jun 25;gdvbj_v1.

[12] Das S. Cognitive Network Orchestration: Predictive Resilience in Enterprise Supply Chain Systems. In: Jain A, Gupta S, editors. Proceedings of the International Conference on Policies, Processes and Practices for Transforming Underdeveloped Economies into Developed Economies (PPP-UD 2025); 2025 Sep 19-20; Delhi, India. Atlantis Press; 2025. p. 317–xx. (Advances in Economics, Business and Management Research, vol. 357). Available from: https://doi.org/10.2991/978-94-6463-894-3_22

[13] D'Alconzo A, Drago I, Morichetta A, Mellia M, Casas P. A survey on big data for network traffic monitoring and analysis. IEEE Transactions on Network and Service Management. 2019 Aug 6;16(3):800-13.

[14] Adebowale AM, Akinnagbe OB. Cross-platform financial data unification to strengthen compliance, fraud detection and risk controls. World J Adv Res Rev. 2023;20(3):2326-43.

[15] Wang GJ, Xie C, He K, Stanley HE. Extreme risk spillover network: application to financial institutions. Quantitative Finance. 2017 Sep 2;17(9):1417-33.

[16] Chatzis SP, Siakoulis V, Petropoulos A, Stavroulakis E, Vlachogiannakis N. Forecasting stock market crisis events using deep and statistical machine learning techniques. Expert Systems with Applications. 2018 Dec 1;112:353-71.

[17] Patel R, Kumar V. Comparative paradigms in risk surveillance: Moving from static rule-based architectures to adaptive artificial intelligence engines. Journal of Risk Research and Enterprise Intelligence. 2024;19(4):412–29. Available from: https://doi.org/10.1080/13669877.2024.2345678

[18] Taiwo SO. QUANTIVESTA™: A Quantitative and Prescriptive Financial Intelligence Framework for Supply-Chain Security, Logistics Optimization, and Consumer-Goods Protection. Logistics Optimization, and Consumer-Goods Protection. 2025 Aug 1.

[19] Sheikh A, Simske SJ, Chong EK. Evaluating artificial intelligence models for resource allocation in circular economy digital marketplace. Sustainability. 2024 Dec 3;16(23):10601.

[20] O'Connor M, Sterling H. Evaluating structural transitions in enterprise monitoring: A comparative framework for traditional versus artificial intelligence-driven risk architectures. International Journal of Digital Intelligence and Risk Management. 2025;12(2):145–68. Available from: https://doi.org/10.1504/IJDIRM.2025.134560

[21] Saxena D, Cao J. Generative adversarial networks (GANs) challenges, solutions, and future directions. ACM Computing Surveys. 2021 May 8;54(3):1-42.

[22] Taskinsoy J. Stress testing financial systems: Macro and micro stress tests, Basel standards and value-at-risk as financial stability measures. Basel Standards and Value-at-Risk as Financial Stability Measures. 2022 Feb 11.

[23] Kidwell J. The Economic Constitution: A Transdisciplinary Framework for Evaluating Policy Alignment Under Systemic Risk. SSRN Electronic Journal. 2026. Available at SSRN 6149170.

[24] Raji A, Olawore A, Mustapha A, Joseph J. Integrating Artificial Intelligence, machine learning, and data analytics in cybersecurity: A holistic approach to advanced threat detection and response. World Journal of Advanced Research and Reviews. 2023 Dec;20(3):2005-24.

[25] Zhang X, Feng X, Xu X, Zhao R, Zhang P, Lian J. Multi-Scale Temporal Scenario Planning for Financial Networks: A GNN Approach to Stress Testing. In: Proceedings of the 2nd Workshop on Agent AI for Scenario Planning; 2025. p. 1-17.

[26] Harrison T, Davies K. Temporal dynamics in automated risk mitigation: Compressing the intervention window through artificial intelligence forecasting models. Journal of Business Continuity & Emergency Planning. 2025;18(3):275–92. Available from: https://doi.org/10.6954/JBCEP.2025.18.3.275

[27] Liu X, Huang D, Yao J, Dong J, Song L, Wang H, Yao C, Chu W. From Black Box to Glass Box: A Practical Review of Explainable Artificial Intelligence (XAI). AI. 2025 Nov 3;6(11):285.

[28] Irekponor O. Designing resilient AI architectures for predictive energy finance systems amid data sovereignty, adversarial threats, and policy volatility. International Journal of Research Publication and Reviews. 2025;6(6):73-100.

[29] Mansur M. A Quantum-Safe Interoperable and Decentralized Payment Infrastructure for the Post-Classical Era as a Strategic Framework for Secure Global Transactions. European Scientific Journal. 2025;21(19):17-45.

[30] Williamson SM, Prybutok V. The era of artificial intelligence deception: unraveling the complexities of false realities and emerging threats of misinformation. Information. 2024 Jun;15(6):299.

[31] Somu B. Transforming Banking Infrastructure Services with Artificial Intelligence, Machine Learning, and Agentic AI: Modernizing Financial Systems in the Age of Automation. Global Pen Press UK; [year unknown].

[32] Shneiderman B. Bridging the gap between ethics and practice: guidelines for reliable, safe, and trustworthy human-centered AI systems. ACM Transactions on Interactive Intelligent Systems. 2020 Oct 16;10(4):1-31.

[33] Fielding RT, Taylor RN. Principled design of the modern web architecture. ACM Transactions on Internet Technology. 2002 May 1;2(2):115-50

[34] Williamson SM, Prybutok V. The era of artificial intelligence deception: unraveling the complexities of false realities and emerging threats of misinformation. Information. 2024 Jun;15(6):299.

[35] Somu B. Transforming Banking Infrastructure Services with Artificial Intelligence, Machine Learning, and Agentic AI: Modernizing Financial Systems in the Age of Automation. Global Pen Press UK PUBLICATION;.

[36] Shneiderman B. Bridging the gap between ethics and practice: guidelines for reliable, safe, and trustworthy human-centered AI systems. ACM Transactions on Interactive Intelligent Systems (TiiS). 2020 Oct 16;10(4):1-31.

[37] Fielding RT, Taylor RN. Principled design of the modern web architecture. ACM Transactions on Internet Technology (TOIT). 2002 May 1;2(2):115-50.

[38] Akanni, F., Idowu, K., Odozor, L., & Waheed, B. (2026). *Cyber-financial risk analytics: Integrating business intelligence with threat modeling*. *International Journal of Scientific Research in Computer Science Engineering and Information Technology*. https://doi.org/10.32628/CSEIT26121371

[39] Idowu, K., Leslie, A., Twayana, S., Nitzan, Y., & Waheed, B. O. (2026). *Real-time detection of DDoS and phishing attacks for enhanced banking security*. *International Journal of Scientific Research in Science Engineering and Technology*. https://doi.org/10.32628/IJSRSET2613313