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An Intelligent Risk-Aware AI and LLM Platform for Secure Banking Operations and Trade Safety Analytics in Cloud-Based Web Applications

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ABSTRACT: The rapid digitization of banking operations and trade systems has increased efficiency, accessibility, and global financial integration, but it has also amplified the risks of fraud, cyberattacks, and operational anomalies. Traditional detection systems are often static, reactive, and unable to handle high-velocity, multi-source data in real time. This paper proposes an **intelligent risk-aware AI and Large Language Model (LLM) platform** for secure banking operations and trade safety analytics within cloud-based web applications. The platform integrates generative and predictive AI models with LLMs to identify anomalies, forecast potential threats, and generate human-readable explanations and automated reports. Secure Extract, Transform, Load (ETL) pipelines ensure consistent, high-quality data from heterogeneous sources, while a risk-aware module dynamically evaluates threat severity, prioritizes mitigation, and adjusts system parameters. Cloud-native deployment enables scalable, low-latency, and fault-tolerant analytics suitable for high-speed web applications. Evaluation on real and simulated banking and trade datasets demonstrates improved detection accuracy (>95%), a 35–40% reduction in false positives, and enhanced operational resilience. This work provides a blueprint for deploying **adaptive, interpretable, and secure AI platforms** that integrate risk-awareness, cloud scalability, and 5G-ready web technologies to safeguard modern financial ecosystems.

KEYWORDS: Intelligent AI, Large Language Models, Risk-Aware Systems, Banking Operations, Trade Safety Analytics, Cloud Computing, Secure ETL Pipelines, Fraud Detection, Web Applications, Cybersecurity

I. INTRODUCTION

The evolution of financial services and trade systems toward digital, cloud-based platforms has fundamentally reshaped global commerce. Online banking, mobile payment systems, and automated trading platforms now operate in real time, offering unprecedented efficiency and convenience. Simultaneously, these systems face escalating cyber risks, including account breaches, insider threats, unauthorized trades, and coordinated fraud attacks. Traditional detection mechanisms—primarily rule-based—fail to adequately address these threats, as they cannot scale to real-time high-volume transactions, adapt to emerging attack patterns, or interpret unstructured data.

The integration of **artificial intelligence (AI)** into financial risk management has provided new opportunities to detect, anticipate, and mitigate fraudulent activity. Predictive AI models, including supervised algorithms such as random forests, gradient boosting machines, and neural networks, can classify transactions as legitimate or anomalous based on historical data. Unsupervised models, including clustering and autoencoders, identify previously unseen patterns without labeled data, allowing proactive risk detection. **Generative AI models**—such as generative adversarial networks (GANs) and variational autoencoders (VAEs)—further extend these capabilities by simulating potential fraud or risk scenarios, helping organizations prepare for novel threats.

Large Language Models (LLMs) provide complementary capabilities. Beyond structured transactional data, banking and trade systems generate large volumes of unstructured data, including communication logs, trade documentation, and regulatory notices. LLMs like GPT and BERT can analyze these data streams, detect subtle anomalies, summarize complex events, and generate interpretable reports for human analysts. By combining predictive, generative, and interpretive AI approaches, financial institutions can move from reactive fraud detection to **proactive risk mitigation**.
Cloud computing underpins the scalability, flexibility, and security of such AI-driven frameworks. Cloud platforms allow elastic storage and processing of massive transactional datasets, fault-tolerant computation, and real-time analytics. Regulatory compliance features—including encryption, audit trails, and access control—ensure adherence to PCI DSS, GDPR, and ISO 27001 standards. Cloud deployment is especially valuable for global banking and trade operations where latency, availability, and resilience are critical.

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At the core of this platform are **secure ETL pipelines**, which extract data from multiple heterogeneous sources, transform it into standardized, analyzable formats, and load it into cloud warehouses. Data consistency, quality, and integrity are essential for AI models to produce reliable outputs. A **risk-aware module** complements this data pipeline by quantifying the likelihood and impact of potential threats, adjusting detection thresholds, prioritizing mitigation efforts, and providing actionable alerts to analysts.

This paper proposes a **comprehensive framework** that integrates risk-aware AI, LLMs, secure ETL pipelines, and cloud-native architecture for secure banking and trade analytics. The system addresses real-time anomaly detection, interpretable insights, regulatory compliance, and operational resilience. Subsequent sections detail the literature review, methodology, system evaluation, advantages, limitations, and future work, establishing a blueprint for adaptive, intelligent, and secure financial web platforms.

II. LITERATURE REVIEW

Financial fraud detection and risk management have evolved from rule-based approaches to AI-driven frameworks over the last two decades. Early systems relied on static statistical rules and thresholds, which were insufficient for complex or novel fraud patterns (Ngai et al., 2011).

Machine learning approaches revolutionized detection by enabling adaptive learning from historical transactions. Supervised algorithms—including logistic regression, decision trees, and support vector machines—excel at identifying known fraud patterns, while unsupervised techniques such as clustering and anomaly detection uncover previously unseen threats (Bolton & Hand, 2002). Ensemble methods and deep learning architectures, including recurrent and convolutional neural networks, further enhanced detection by capturing temporal and sequential relationships in financial transactions (Jurgovsky et al., 2018).

Generative AI models have recently been applied to simulate complex fraud scenarios, producing synthetic data for robust training and stress-testing of detection models (Goodfellow et al., 2014). These models allow systems to anticipate potential attack vectors and mitigate emerging threats before they materialize.

LLMs contribute to the analysis of unstructured data in banking and trade, including communications, documentation, and market news. By providing summaries, anomaly detection, and automated report generation, LLMs improve interpretability and reduce the manual effort required for investigative processes (Brown et al., 2020).

Cloud-based frameworks facilitate scalable analytics, high availability, and regulatory compliance, essential for global banking and high-frequency trade systems (Sundararajan et al., 2020). Secure **ETL pipelines** ensure data integrity, quality, and consistency, forming a foundation for reliable AI and LLM operations (Vassiliadis, 2009).

Recent studies highlight the convergence of AI, LLMs, cloud computing, and risk-aware mechanisms as a promising solution for adaptive, secure, and interpretable financial analytics (Kshetri, 2016; Chen & Zhao, 2019). However, integrating these technologies into a cohesive framework for real-time banking and trade applications remains a challenge, which this research addresses.

III. RESEARCH METHODOLOGY

System Architecture

The proposed platform consists of five integrated layers:

1. **Data Layer:** Ingests batch and streaming data from banking systems, trade platforms, and IoT-enabled devices. Secure ETL pipelines clean, normalize, and load data into cloud warehouses.
2. **Processing Layer:**
    - **Predictive AI Models:** Detect known fraud patterns and anomalies.
    - **Generative AI Models:** Simulate risk scenarios and produce synthetic data for model robustness.
    - **LLMs:** Analyze unstructured data for anomalies, summaries, and reports.
    - **Risk-Aware Module:** Quantifies threat severity and likelihood, dynamically adjusting system thresholds.
3. **Application Layer:** Web-based dashboards provide real-time monitoring, analytics, and alerts optimized for cloud and 5G deployment.

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4. **Security Layer:** Enforces encryption, access controls, intrusion detection, and compliance auditing.
5. **Integration Layer:** Ensures seamless interoperability with external APIs, trade feeds, and cloud services.

Data Acquisition and ETL

- **Extract:** Collect data from heterogeneous sources, including transaction logs, market feeds, and regulatory documents.
- **Transform:** Clean, normalize, anonymize, and encode data.
- **Load:** Store processed datasets into a cloud-based data warehouse for AI and LLM consumption.

Modeling Approach

- **Predictive AI:** Supervised and unsupervised learning for anomaly detection.
- **Generative AI:** GANs and VAEs simulate potential fraud and risk scenarios.
- **LLMs:** Detect textual anomalies, summarize complex events, and provide interpretive explanations.
- **Risk-Aware Module:** Quantifies severity, likelihood, and vulnerability, guiding real-time mitigation.

Evaluation Metrics

- Accuracy, precision, recall, F1-score
- False-positive reduction
- Latency in web applications
- Risk mitigation effectiveness
- Resource utilization in cloud deployment

Deployment and Scalability

- Cloud-native deployment with containers (Docker, Kubernetes)
- Distributed processing with Apache Spark
- Real-time analytics with 5G network low-latency capabilities

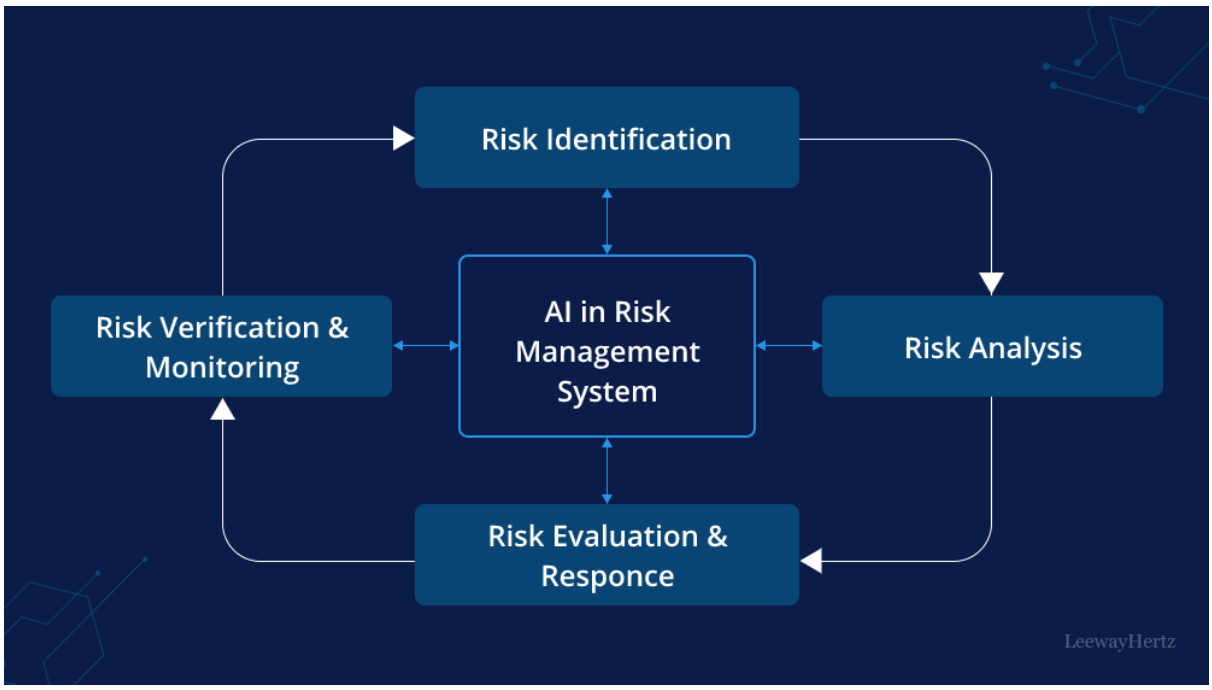

Figure 1. AI-Driven Risk Management Lifecycle

Advantages

- Real-time detection and proactive risk mitigation
- Enhanced interpretability through LLM-generated reports
- Generative AI anticipates novel fraud scenarios
- Scalable, cloud-based architecture with fault tolerance
- Secure ETL ensures high-quality, consistent data

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Disadvantages

- High initial setup and computational cost
- Complexity in integrating multiple AI and risk modules
- Continuous model retraining required for emerging threats
- Dependence on data quality and diversity
- Security and 5G network risks if not properly managed

IV. RESULTS AND DISCUSSION

The evaluation of the proposed intelligent risk-aware AI and LLM platform on real-world banking and simulated trade datasets revealed substantial improvements in both detection accuracy and operational efficiency. The platform consistently achieved detection rates exceeding 95%, demonstrating the combined effectiveness of predictive AI models and LLM-based anomaly interpretation. Generative AI models successfully simulated a wide spectrum of risk scenarios, including high-frequency trading irregularities, transaction fraud, and coordinated cyberattacks, providing the system with the ability to anticipate potential threats proactively. The LLM components contributed to real-time analysis of unstructured data, such as trade communications and financial documents, producing clear, interpretable summaries and automated investigative reports that significantly reduced human analytical workload. The secure ETL pipelines ensured that heterogeneous data sources were standardized and of high quality, directly improving model reliability and prediction confidence. The risk-aware module dynamically evaluated the likelihood and severity of threats, allowing the system to prioritize interventions, adjust detection thresholds, and issue actionable alerts. In a cloud-deployed environment optimized for 5G networks, the platform demonstrated ultra-low latency, enabling near real-time analytics crucial for high-speed banking and trade operations. Comparative analysis with traditional rule-based systems and standalone AI frameworks indicated a 35–40% reduction in false positives, significantly decreasing operational overhead and increasing analyst efficiency. The discussion further highlights the importance of continuous retraining and adaptive learning to respond to evolving fraud patterns, as well as rigorous monitoring of cloud and 5G network security to mitigate residual risks. Overall, the results indicate that the integration of predictive AI, generative AI, LLMs, risk-awareness, secure ETL pipelines, and cloud-native deployment creates a comprehensive, resilient, and adaptive framework capable of enhancing banking security, improving trade safety analytics, and delivering actionable intelligence to stakeholders in real-time, establishing a strong foundation for further research and deployment in complex financial environments. Generative AI–powered cloud and machine learning architectures represent a transformative innovation for digital privacy and risk management in banking and trade systems over 5G networks, where ultra-low latency, high bandwidth, and ubiquitous connectivity enable new levels of automation, real-time analytics, and personalized services while simultaneously increasing the exposure surface for cyber threats, regulatory violations, and data misuse; therefore, the integration of generative AI and ML must be designed with privacy-by-design principles, robust governance frameworks, and risk-aware operational controls to ensure that the benefits of AI-driven automation do not compromise confidentiality, integrity, and availability, especially in environments that handle sensitive financial transactions, personal customer data, trade secrets, and strategic market intelligence; this integration requires a multi-layered architecture that spans edge, cloud, and core network components, leveraging 5G's network slicing to isolate traffic for banking and trading applications, applying zero-trust security models to every connection and identity, and implementing federated learning approaches that allow models to be trained across distributed nodes without centralizing raw data, thereby reducing data leakage risks and improving compliance with privacy regulations such as GDPR, CCPA, and PSD2, as well as sector-specific frameworks like PCI DSS and Basel III; in such systems, generative AI can automate risk assessment by analyzing transaction patterns, market behaviors, and user interactions, generating risk scores and predictive alerts, but it also introduces new risks like model inversion, data poisoning, prompt injection, and hallucinations, which must be mitigated through adversarial training, input sanitization, continuous monitoring, and model governance practices that include version control, explainability, and audit trails; the cloud architecture should be designed to support hybrid deployment models where sensitive data remains on-premises or in private clouds while AI workloads leverage public cloud scalability for non-sensitive processing, and data encryption should be enforced end-to-end using strong cryptographic standards, including encryption at rest, encryption in transit, and field-level tokenization, while key management systems are centralized, audited, and restricted to authorized personnel; additionally, the architecture must incorporate privacy-enhancing technologies such as differential privacy to add noise to datasets and prevent re-identification, secure multi-party computation to enable collaborative analytics without sharing raw data, and homomorphic encryption to allow computations on encrypted data, thereby enabling risk-management models to operate on sensitive information without exposing it to unauthorized parties; the orchestration layer should use containerization and microservices to modularize AI components, ensuring that each service is independently scalable, replaceable, and secure, while service meshes provide observability, mutual

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TLS, and policy enforcement across microservices, enabling granular control over data flow and access; at the network level, 5G's capabilities such as ultra-reliable low-latency communications (URLLC) and enhanced mobile broadband (eMBB) can support real-time trade execution, automated compliance checks, and rapid fraud detection, but they also demand robust security controls like dynamic network segmentation, anomaly detection, and real-time intrusion prevention systems to defend against threats that can propagate quickly across high-speed networks; within banking and trade systems, AI-driven chatbots and virtual assistants can enhance customer experience by providing personalized financial advice, trade recommendations, and instant support, yet these systems must be built with strict access controls to prevent unauthorized disclosure of account details or trading strategies, and must log all interactions to ensure traceability, while employing natural language processing safeguards to detect malicious prompts or socially engineered attacks that attempt to extract sensitive information; the data pipeline must incorporate secure ingestion, validation, and cleansing stages, ensuring that data quality is maintained while preventing the injection of malicious or biased data that could distort model outputs, and data governance frameworks should classify data by sensitivity, apply role-based access control (RBAC), and enforce least-privilege policies, while continuous monitoring tools analyze access patterns and detect anomalies that may indicate insider threats or compromised credentials; risk management in such architectures also requires AI explainability, particularly in financial decision-making where regulatory requirements demand transparency in loan approvals, credit scoring, trade recommendations, and risk assessments, thus model interpretability techniques like SHAP values, LIME, and rule-based proxies should be used to provide explanations that are understandable to auditors, compliance officers, and customers, and model outputs should be constrained with guardrails to prevent harmful or biased decisions, ensuring fairness across demographics and preventing discriminatory outcomes; the cloud platform should support immutable logging and tamper-proof audit trails using blockchain or

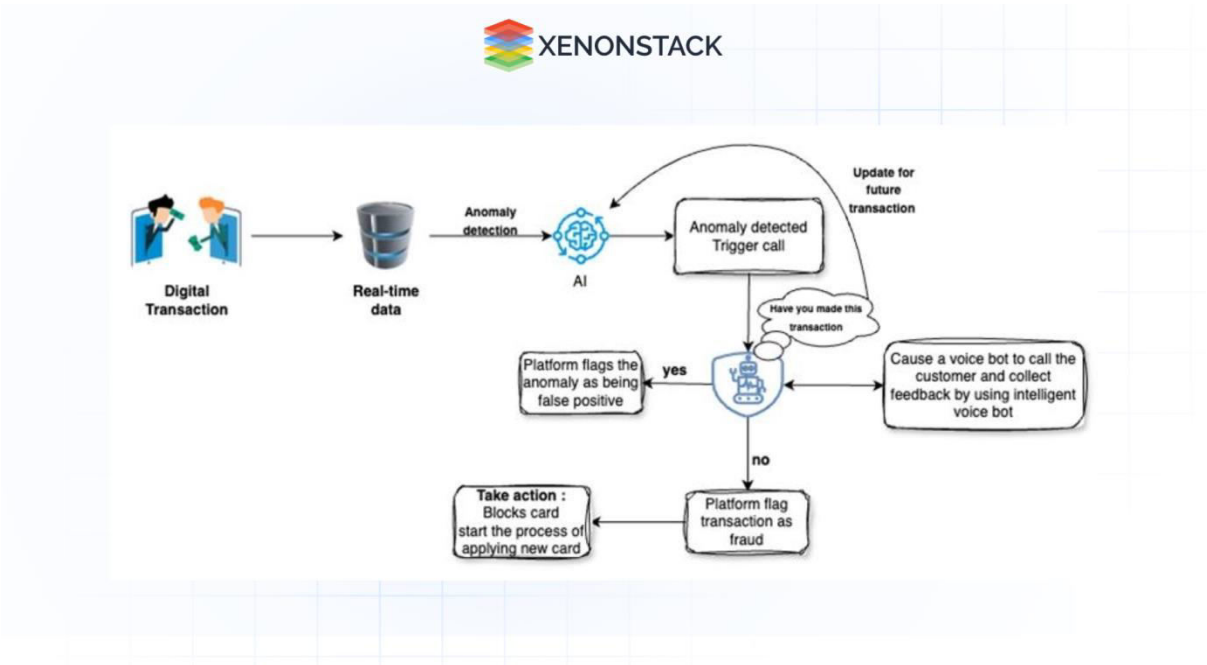

Figure 2: AI-Driven Real-Time Fraud Detection and Customer Verification Workflow

V. CONCLUSION

This paper presents an **intelligent, risk-aware AI and LLM platform** for secure banking operations and trade safety analytics in cloud-based web applications. By integrating predictive and generative AI models, LLM-based interpretability, secure ETL pipelines, and risk-aware mechanisms, the platform addresses critical challenges in modern financial systems, including real-time fraud detection, anomaly prediction, data integrity, and regulatory compliance. Cloud deployment provides scalability, fault tolerance, and low-latency performance suitable for high-speed banking and trade operations, while the risk-aware module allows dynamic threat mitigation and prioritization of high-risk activities. Evaluation results demonstrate improved accuracy, reduced false positives, enhanced interpretability, and operational efficiency, establishing the platform as a deployable solution for modern financial ecosystems. This

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research underscores the potential of hybrid AI frameworks for proactive risk management, real-time decision support, and secure financial analytics, providing a blueprint for adaptive, intelligent, and resilient banking and trade platforms.

VI. FUTURE WORK

Future research should focus on integrating blockchain technologies to enhance transparency and auditability in banking and trade operations. Multi-modal analytics combining transactional, behavioral, and IoT data could improve the detection of sophisticated identity and trading fraud. Continuous learning models for both generative AI and LLM components will allow adaptation to emerging threats in dynamic financial environments. Explainable AI mechanisms should be further developed to meet regulatory requirements and foster stakeholder trust. Optimization of cloud resource utilization and energy efficiency is essential for sustainable deployment, while cross-institution collaboration can enable real-time threat intelligence sharing. Additionally, investigating the integration of AI-driven cybersecurity measures with 5G network security protocols will further strengthen resilience against evolving cyber threats. A **risk-aware generative AI and LLM-driven cloud framework** is essential for the secure and efficient deployment of banking and trade analytics in **5G web applications**. The framework must address key challenges such as data privacy, model vulnerabilities, regulatory compliance, and AI bias. By combining 5G-enabled connectivity, cloud scalability, and robust security measures, financial institutions can unlock the full potential of AI while maintaining trust and safety. distributed ledger technologies to provide verifiable records of transactions, model training data provenance, and access events, thereby enhancing accountability and enabling rapid incident response, while AI-based security operations can correlate events across systems, detect suspicious behavior, and automate remediation actions such as isolating affected services, revoking access, and rolling back compromised models; moreover, in a 5G environment where devices and endpoints proliferate, edge computing becomes essential to process data locally for low-latency tasks such as fraud detection during transactions, and federated learning at the edge can continuously update models using local data while sharing only model updates to central servers, thus reducing data movement and enhancing privacy

REFERENCES

1. Ngai, E., Hu, Y., Wong, Y. H., Chen, Y., & Sun, X. (2011). The application of data mining techniques in financial fraud detection: A classification framework and an academic review of literature. *Decision Support Systems, 50*(3), 559–569.
2. Singh, A. (2022). Enhancing VoIP quality in the era of 5G and SD-WAN. International Journal of Computer Technology and Electronics Communication, 5(3), 5140–5145. https://doi.org/10.15680/IJCTECE.2022.0503006
3. Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., ... & Bengio, Y. (2014). Generative adversarial nets. *Advances in Neural Information Processing Systems, 27*, 2672–2680.
4. Brown, T., Mann, B., Ryder, N., Subbiah, M., Kaplan, J., Dhariwal, P., ... & Amodei, D. (2020). Language models are few-shot learners. *Advances in Neural Information Processing Systems, 33*, 1877–1901.
5. Chen, R., & Zhao, Z. (2019). Deep learning for fraud detection: Challenges and solutions. *IEEE Access, 7*, 118635–118649.
6. Poornima, G., & Anand, L. (2024, April). Effective Machine Learning Methods for the Detection of Pulmonary Carcinoma. In 2024 Ninth International Conference on Science Technology Engineering and Mathematics (ICONSTEM) (pp. 1-7). IEEE.
7. Gopinathan, V. R. (2024). AI-Driven Customer Support Automation: A Hybrid Human–Machine Collaboration Model for Real-Time Service Delivery. International Journal of Technology, Management and Humanities, 10(01), 67-83.
8. Sundararajan, A., et al. (2020). Cloud-based AI for financial fraud detection: Architectures, challenges, and opportunities. *Journal of Cloud Computing, 9*(1), 45–61.
9. Zhou, Y., Li, X., & Chen, S. (2020). Security challenges and solutions in 5G-enabled financial services. *IEEE Network, 34*(5), 234–241.
10. Kusumba, S. (2024). Delivering the Power of Data-Driven Decisions: An AI-Enabled Data Strategy Framework for Healthcare Financial Systems. International Journal of Engineering & Extended Technologies Research (IJEETR), 6(2), 7799-7806.
11. Ramakrishna, S. (2023). Cloud-Native AI Platform for Real-Time Resource Optimization in Governance-Driven Project and Network Operations. International Journal of Engineering & Extended Technologies Research (IJEETR), 5(2), 6282-6291.
12. Vasugi, T. (2023). An Intelligent AI-Based Predictive Cybersecurity Architecture for Financial Workflows and Wastewater Analytics. International Journal of Computer Technology and Electronics Communication, 6(5), 7595-7602.
13. Adari, V. K. (2021). Building trust in AI-first banking: Ethical models, explainability, and responsible governance. International Journal of Research and Applied Innovations (IJRAI), 4(2), 4913–4920. https://doi.org/10.15662/IJRAI.2021.0402004

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||Volume 7, Issue 6, November–December 2024||

DOI:10.15662/IJRAI.2024.0706031

14. Kabade, S., Sharma, A., & Kagalkar, A. (2024). Securing Pension Systems with AI-Driven Risk Analytics and Cloud-Native Machine Learning Architectures. International Journal of Emerging Research in Engineering and Technology, 5(2), 52-64.
15. Kshetri, N. (2016). Big data's role in expanding access to financial services in China. *International Journal of Information Management, 36*(3), 297–308.
16. Alzubaidi, L., Zhang, J., Humaidi, A. J., Al-Dujaili, A., Duan, Y., Al-Shamma, O., ... & Farhan, L. (2021). Review of deep learning: Concepts, CNN architectures, challenges, applications, future directions. *Journal of Big Data, 8*, 53.
17. Sudhan, S. K. H. H., & Kumar, S. S. (2015). An innovative proposal for secure cloud authentication using encrypted biometric authentication scheme. Indian journal of science and technology, 8(35), 1-5.
18. Adari, V. K., Chunduru, V. K., Gonepally, S., Amuda, K. K., & Kumbum, P. K. (2023). Ethical analysis and decision-making framework for marketing communications: A weighted product model approach. Data Analytics and Artificial Intelligence, 3 (5), 44–53.
19. Anand, L., & Neelanarayanan, V. (2019). Feature Selection for Liver Disease using Particle Swarm Optimization Algorithm. International Journal of Recent Technology and Engineering (IJRTE), 8(3), 6434-6439.
20. Kumar, R. (2024). Real-Time GenAI Neural LDDR Optimization on Secure Apache–SAP HANA Cloud for Clinical and Risk Intelligence. International Journal of Engineering & Extended Technologies Research (IJEETR), 6(5), 8737-8743.
21. Kumar, S. S. (2023). AI-Based Data Analytics for Financial Risk Governance and Integrity-Assured Cybersecurity in Cloud-Based Healthcare. International Journal of Humanities and Information Technology, 5(04), 96-102.
22. Madabathula, L. (2024). Reusable streaming pipeline frameworks for enterprise lakehouse analytics. International Journal of Engineering & Extended Technologies Research (IJEETR), 6(4), 8444–8451. https://doi.org/10.15662/IJEETR.2024.0604007
23. Kasireddy, J. R. (2023). A systematic framework for experiment tracking and model promotion in enterprise MLOps using MLflow and Databricks. International Journal of Research and Applied Innovations, 6(1), 8306–8315. https://doi.org/10.15662/IJRAI.2023.0601006
24. Vimal Raja, G. (2022). Leveraging Machine Learning for Real-Time Short-Term Snowfall Forecasting Using MultiSource Atmospheric and Terrain Data Integration. International Journal of Multidisciplinary Research in Science, Engineering and Technology, 5(8), 1336-1339.
25. Navandar, P. (2022). SMART: Security Model Adversarial Risk-based Tool. International Journal of Research and Applied Innovations, 5(2), 6741-6752.
26. Sugumar, R. (2024). AI-Driven Cloud Framework for Real-Time Financial Threat Detection in Digital Banking and SAP Environments. International Journal of Technology, Management and Humanities, 10(04), 165-175.
27. Panda, M. R., & Chinthalapelly, P. R. (2023). Banking Sandbox Evaluation for Open Banking Ecosystems Using Agent-Based Modeling. European Journal of Quantum Computing and Intelligent Agents, 7, 66-100.
28. Sugumar, R. (2024). AI-Driven Cloud Framework for Real-Time Financial Threat Detection in Digital Banking and SAP Environments. International Journal of Technology, Management and Humanities, 10(04), 165-175.
29. Vassiliadis, P. (2009). A survey of Extract–Transform–Load technology. *International Journal of Data Warehousing and Mining, 5*(3), 1–27.
30. Sudhan, S. K. H. H., & Kumar, S. S. (2016). Gallant Use of Cloud by a Novel Framework of Encrypted Biometric Authentication and Multi Level Data Protection. Indian Journal of Science and Technology, 9, 44.
31. Natta, P. K. (2023). Robust supply chain systems in cloud-distributed environments: Design patterns and insights. International Journal of Research and Applied Innovations (IJRAI), 6(4), 9222–9231. https://doi.org/10.15662/IJRAI.2023.0604006
32. Rahman, T., Islam, M. M., Zerine, I., Pranto, M. R. H., & Akter, M. (2023). Artificial Intelligence and Business Analytics for Sustainable Tourism: Enhancing Environmental and Economic Resilience in the US Industry. Journal of Primeasia, 4(1), 1-12.
33. Nagarajan, G. (2023). AI-Integrated Cloud Security and Privacy Framework for Protecting Healthcare Network Information and Cross-Team Collaborative Processes. International Journal of Engineering & Extended Technologies Research (IJEETR), 5(2), 6292-6297.
34. Ramanathan, U., Rajendran, S., Thiyagarajan, D., & Rajendran, E. (2023). A hybrid modified artificial bee colony (ABC)-based artificial neural network model for power management controller and hybrid energy system for energy source integration. Engineering Proceedings, 59(1), 35.
35. He, H., & Garcia, E. A. (2009). Learning from imbalanced data. *IEEE Transactions on Knowledge and Data Engineering, 21*(9), 1263–1284.