A Survey of Cloud-Enabled Machine Learning in Financial Services

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Abstract

The integration of cloud computing and machine learning (ML) is reshaping financial services by enabling scalable, real-time, data-driven decision-making. This survey reviews cloud-enabled machine learning (ML) developments from 2021 to 2025, with a focus on financial sector applications. Cloud services provide elastic computing, distributed training, and low-latency analytics, which are essential for processing large-scale financial datasets. Financial institutions increasingly leverage these capabilities to enhance credit scoring, fraud detection, risk forecasting, and customer personalization. Advances in deep learning, ensemble methods, federated learning, automated ML, and explainable AI (XAI) are improving model accuracy, operational transparency, and regulatory compliance. MLOps pipelines further streamline the deployment, monitoring, and lifecycle management of ML models in dynamic environments. Key challenges persist, including data privacy, integrating legacy systems, regulatory constraints, and latency-sensitive operations. This survey categorizes the literature into four themes. (i) Cloud architecture and service models tailored for ML workflows, (ii) supervised and unsupervised ML techniques applied in finance, (iii) comparative analysis of real-world use cases, and (iv) performance evaluation metrics and trade-offs. Unlike prior reviews, this review uniquely synthesizes recent trends across cloud-native ML technologies and maps their practical implications in regulated financial environments. Future directions include exploring edge-cloud coordination for time-critical tasks, building robust models against adversarial data, implementing privacy-preserving mechanisms, and establishing standardized governance frameworks. This survey serves as a comprehensive reference for researchers and practitioners seeking to leverage cloud-based machine learning (ML) in financial services.

Keywords: *Computing, Financial Analytics, Machine Learning, Real-Time Data Processing*

1. Introduction

The financial services industry is undergoing a profound transformation driven by the exponential growth of data and the increasing demand for real-time,

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intelligent analytics. This shift is particularly relevant today as institutions adapt to increased competition, heightened regulatory scrutiny, and evolving customer expectations. The convergence of cloud computing and machine learning (ML) has emerged as a critical enabler for navigating this complex landscape.

While global data is projected to expand from 44 zettabytes in 2020 to 163 zettabytes by 2025 [1], financial data, which ranges from high-frequency trading to customer transactions, constitutes a significant portion of this growth. Traditional IT systems struggle to handle such scale efficiency [2].

Cloud computing addresses this gap by providing elastic, on-demand infrastructure that accelerates deployment, improves cost-efficiency, and supports scalable analytics. Consequently, many financial institutions have adopted hybrid or public cloud models to modernize operations and reduce infrastructure overhead [3], [4].

Between 2021 and 2025, significant advancements have been observed in both cloud infrastructure capabilities and ML algorithms tailored for finance[5]. ML offers advantages over traditional statistical models by detecting non-linear relationships and enabling more accurate forecasting [6]. Applications have extended beyond risk scoring to fraud detection, algorithmic trading, and robo-advisory. The synergy is clear, where cloud platforms offer compute and storage elasticity, ML delivers the analytical power to derive insights from vast, complex datasets [7].

However, challenges remain. Financial data demands stringent privacy controls, including encryption, data localization, and federated learning architectures [8]. The opacity of many ML models raises concerns about explainability and accountability, especially in regulated environments. Operational issues such as integrating with legacy systems and ensuring low latency persist [9]. Mitigation efforts include adopting multi-cloud strategies, leveraging edge computing for latency-sensitive tasks, and exploring secure data-sharing frameworks like blockchain [10].

This survey reviews developments from 2021 to 2025, focusing on cloud-enabled ML applications in financial services. The scope includes cloud architectures, ML methods deployed on cloud platforms, key application domains, and comparative performance insights. Section II reviews cloud infrastructure, Section III examines ML techniques, Section IV explores applications, Section V provides performance comparisons, and Section VI concludes with future research directions.

2. Cloud Computing

Cloud computing underpins the infrastructure for modern big data analytics in financial services. This section outlines cloud service models, deployment strategies, technical enablers critical to supporting advanced financial applications, and associated challenges.

2.1 Cloud Infrastructure and Services in Finance

Financial institutions increasingly rely on infrastructure-as-a-service (IaaS) and platform-as-a-service (PaaS) offerings to manage data-intensive workloads. Major cloud providers supply scalable compute instances, storage, and managed analytics frameworks, reducing reliance on on-premises systems. Cloud-based data lakes aggregate structured and unstructured data, with platforms such as Google BigQuery and distributed engines like Spark and Hadoop enabling real-time analytics, historical back testing, and batch processing.

A key advancement is the widespread adoption of cloud-native technologies, including containerization, microservices, and serverless computing [11]. Over 75% of financial institutions now deploy containerized workloads, especially in payment processing and fraud detection contexts [12]. Microservices facilitate modular development and scaling, while orchestration tools such as Kubernetes handle load balancing and automated failover. Containerization ensures portability across hybrid and multi-cloud environments.

Serverless computing enables event-triggered functions to run without manual server provisioning, making it ideal for bursty or asynchronous tasks. Hybrid and multi-cloud architectures are common, with sensitive operations running on private infrastructure and public clouds handling high-volume or elastic tasks. Multi-cloud strategies enhance fault tolerance, reduce cost, and leverage vendor-specific capabilities. Tools such as Infrastructure-as-Code (IaC) and unified policy frameworks enable orchestration across environments.

2.2 Challenges and Considerations

Security and compliance remain primary concerns. Financial data requires encryption, fine-grained access control, tokenization, and anonymization. Virtual private networks and identity governance further mitigate risks. Nonetheless, misconfigurations and insider threats necessitate strong cloud governance frameworks.

Privacy-preserving machine learning, such as federated learning and secure multi-party computation, enables collaborative analytics without raw data sharing [13]. These techniques safeguard data privacy but may impact model performance [14].

Latency sensitivity affects applications such as high-frequency trading. Remote data centers introduce delays unsuitable for real-time demands [15]. Edge computing places computation closer to data sources, as in co-located trading servers, enabling fast response and cloud synchronization [16], [17].

Legacy integration poses challenges due to proprietary interfaces and synchronization requirements [18]. Vendor-neutral containerized applications reduce lock-in but often require middleware or custom APIs.

Regulatory compliance demands transparency, auditability, and exit strategies [19]. Institutions must evaluate provider reliability, monitor configurations, and implement risk management practices to mitigate concentration risk.

Lastly, a skilled workforce is critical. Expertise in cloud architecture, DevOps, and data engineering supports secure, scalable adoption [20]. Financial organizations are increasingly investing in upskilling programs to meet evolving infrastructure demands.

Cloud computing forms the technological foundation for ML-driven financial analytics. The following section explores how machine learning models leverage this foundation to deliver value in financial forecasting, fraud detection, and personalization.

3. Machine Learning Techniques

Machine learning underpins financial analytics by enabling scalable modeling on massive datasets through cloud infrastructure. From 2021 to 2025, developments span supervised, unsupervised, and deep learning approaches, with increased automation and integration into cloud-native workflows. This section presents ML methods in order of increasing complexity, with examples and benchmark references to support performance claims. Fig. 1 illustrates a comprehensive end-to-end MLOps architecture that details the functional components and workflows for managing machine learning pipelines in cloud environments.

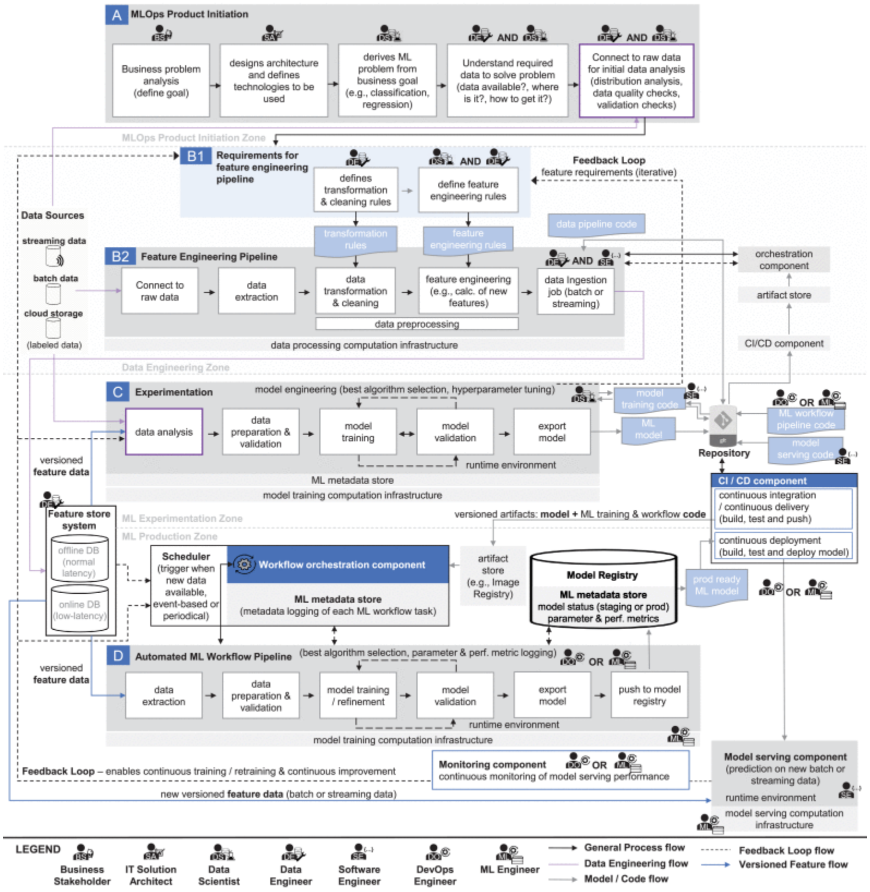

Figure 1. Research Design End-to-end MLOps architecture and workflow with functional components and roles [21]

3.1 Supervised Learning and Predictive Modeling

Supervised learning remains foundational for financial applications such as credit scoring, fraud detection, and asset forecasting. Algorithms like linear regression, decision trees, support vector machines, random forests, and gradient boosting remain prominent. Deep learning models, especially multilayer perceptrons (MLPs) and recurrent neural networks (RNNs) have demonstrated superior accuracy in market forecasting tasks [22].

Long Short-Term Memory (LSTM) networks and Transformer-based models extend sequence modeling for time-series forecasting, capturing long-range dependencies [23]. These models require distributed training on cloud GPUs to manage their computational demands. Probabilistic forecasting is increasingly integrated to estimate uncertainty, particularly in high-volatility scenarios.

Classical models like XGBoost remain preferred in fraud detection due to interpretability and well-defined evaluation metrics [24]. Supervised learning is also enhanced by cloud-based synthetic data generation and federated learning frameworks that expand labeled training sets while preserving privacy.

3.2 Unsupervised Learning and Data-Driven Discovery

Unsupervised learning enables exploratory discovery in unlabeled data. Clustering techniques, such as K-means and DBSCAN, are employed to segment customers or portfolios. Dimensionality reduction methods like PCA and t-SNE extract latent structures, supporting portfolio diversification and stress testing [25].

Anomaly detection models monitor financial transactions for outliers. Autoencoders compute reconstruction errors to flag anomalies, while semi-supervised extensions address cases lacking labeled fraud data. Using tools like Spark Mllib, cloud platforms enable parallelized computation for clustering and anomaly detection over millions of records.

These techniques support automated feature engineering, including asset groupings for sector-based analysis and compressing high-dimensional indicators. Unsupervised models form a precursor stage in pipelines requiring minimal domain assumptions and efficiently scaling in the cloud

3.3 Deep Learning and Advanced AI Techniques

Unsupervised learning enables exploratory discovery in unlabeled data. Clustering techniques, such as K-means and DBSCAN, are employed to segment customers or portfolios. Dimensionality reduction methods like PCA and t-SNE extract latent structures, supporting portfolio diversification and stress testing [25].

i. Deep learning introduces more complex architectures for capturing nonlinear relationships.
ii. Convolutional Neural Networks (CNNs) detect spatial patterns in transformed financial time series data, aiding in volatility prediction and technical chart analysis.
iii. Graph Neural Networks (GNNs) model interconnected financial entities for systemic risk assessment. These require high memory and distributed computing for training on large graphs.
iv. Reinforcement Learning (RL) simulates financial environments for strategy optimization in portfolio management and algorithmic trading, using reward feedback for policy learning
v. Automated Machine Learning (AutoML) streamlines model selection and tuning, and cloud platforms offer rapid prototyping and deployment services.

Explainability is integral to adoption. SHAP values, LIME, and attention-based interpretability are incorporated into model diagnostics. Cloud providers now bunder Explainable AI (XAI) tools with ML workflows. Regulatory frameworks increasingly demand transparency, driving the integration of bias detection and fairness constraints into cloud-based ML pipelines [26].

3.4 Distributed and Scalable ML Pipelines

Operationalizing ML models requires robust pipelines for ingestion, preprocessing, training, validation, and deployment. To enable distributed training, frameworks such as Apache Spark integrate with libraries like MLlib and TensorFlowOnSpark. Parameter server architectures and federated learning strategies are employed for scalable deployment [27]. Fig. 2 illustrates a custom MLOps pipeline tailored for cloud-based financial analytics, showing the full lifecycle from data ingestion to monitoring.

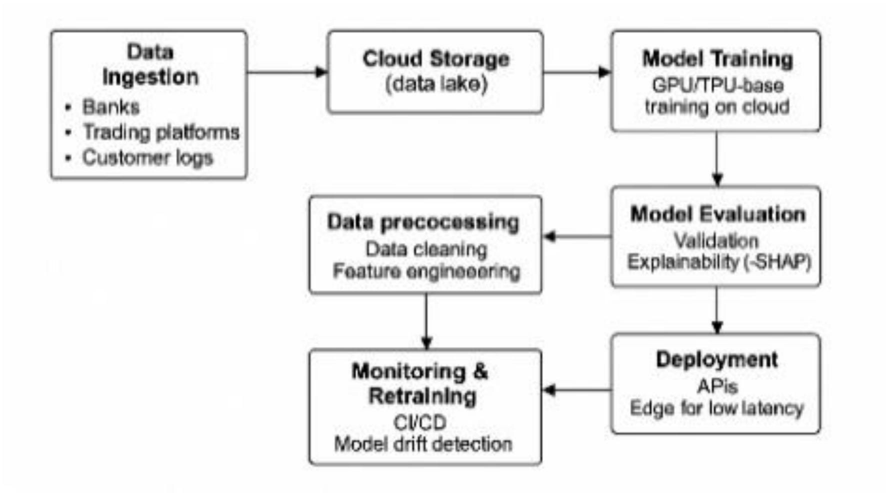

Figure 2. Custom cloud-based MLOps pipeline adapted for financial analytics

Machine Learning-as-a-service (MLaaS) platforms automate experimentation, hyperparameter optimization, and CI/CD practices through MLOps. These platforms offer model registries, linear tracking, and drift detection to support governance and continuous improvement. Cloud environments enable low-latency deployment of simple and complex models to adapt to changing financial data streams.

Financial institutions increasingly rely on infrastructure-as-a-service (IaaS) and platform-as-a-service (PaaS) offerings to manage data-intensive workloads. Major cloud providers supply scalable compute instances, storage, and managed analytics frameworks, reducing reliance on on-premise systems. Cloud-based data lakes aggregate structured and unstructured data, with platforms such as Google BigQuery and distributed engines like Spark and Hadoop enabling real-time analytics, historical backtesting, and batch processing.

4. Applications in Financial Analytics

Cloud-based machine learning (ML) enables scalable, adaptive analytics across critical financial domains. Key applications include fraud detection, risk management, customer analytics, and trending areas such as algorithmic trading. These applications share a common architecture built on real-time data ingestion, explainable ML, and cloud-native model deployment. Table 1 summarizes these key application domains, detailing the associated use cases, machine learning techniques, and the cloud-specific benefits they leverage in financial analytics.

Table 1. Cloud-Enabled Machine Learning Applications in Financial Services

Domain	Use Cases	ML Techniques	Cloud Benefits
Fraud Detection	Transaction scoring, AML, cybersecurity, fraud ring detection	Supervised, Unsupervised, Graph Analytics	Real-time APIs, federated learning, scalibility
Risk Management	Credit scoring, market risk, operational risk	XGBoost, LSTM, Neural Networks	Scalable retraining, scenario testing
Customer Personalization	CLV prediction, churn detection, financial chatbots	Gradient Boosting, Deep Learning NLP	Real-time segmentation, adaptive models
Algorithmic Trading	Price forecasting, portfolio optimization	LSTM, Reinforcement Learning, Gradient Boosting	Low-latency deployment, parallel backtesting

4.1 Fraud Detection and Financial Security

Financial institutions like JPMorgan deploy ML models to detect fraudulent transactions at scale [28]. Supervised learning identifies known fraud signatures, while unsupervised techniques uncover novel threats. Real-time fraud scoring APIs hosted on cloud platforms offer millisecond response times [29]. Graph analytics and pattern mining detect organized fraud rings. AML systems use hybrid rule-based and ML approaches to track suspicious fund movements. Federated learning supports interbank collaboration without violating data privacy. Cloud-based cybersecurity tools apply anomaly detection to network logs, enabling swift mitigation of attacks [30]. Limitations include imbalanced datasets and model drifting due to evolving fraud tactics.

4.2 Risk Management and Regulatory Compliance

ML enhances credit risk scoring by leveraging models such as XGBoost and neural networks, which outperform traditional scorecards. Cloud systems enable dynamic retraining with new borrower data and scenario stress testing via Monte Carlo simulations [31]. Market risk forecasting uses LSTM networks to predict Value-at-Risk (VaR). Operational risk tools analyze logs and communications for compliance breaches. Regulatory bodies adopt cloud-powered SupTech for submission screening and systemic risk alerts. Tools such as AWS SageMaker and Azure ML help banks maintain documentation and audit trails. Limitations include regulatory constraints, data siloing, and the expandability of complex models.

4.3 Anomalies Detection

ML models detect transaction anomalies and known fraud patterns. Supervised learning models dominate when labeled data is available, while unsupervised anomaly detection complements the discovery of novel fraud. Cloud computing enables real-time fraud-scoring APIs with millisecond latency. Graph analytics reveal fraud rings by detecting abnormal substructures. AML detection uses ML to identify structured, layered fund movements. Federated learning enables collaborative model training without exposing raw data. Cybersecurity employs ML classifiers to detect malicious network activity by ingesting real-time logs in the cloud. Model calibration minimizes false positives and prioritizes alerts. Hybrid systems combine rule engines and ML classifiers. Continuous retraining and real-time model deployment on cloud infrastructure enhance adaptability.

4.4 Customer Analytics and Personalization

Cloud ML allows banks to personalize services through segmentation, churn prediction, and recommendation engines. For instance, Bank of America's Erica uses cloud-based Natural Language Processing (NLP) to offer financial advice. Unsupervised clustering adapts to new customer behavior in real time. Gradient boosting models and deep learning forecast Customer Lifetime Value (CLV) and retention risks. Fintechs like Tala use alternative data for credit scoring in underbanked markets. LLMs deployed on cloud platforms power financial chatbots and self-service advisors. However, privacy and consent remain key issues. Secure enclaves and opt-in systems address these challenges under evolving data regulations.

4.5 Algorithmic Trading and Portfolio Optimization

Cloud-based ML models are widely applied in algorithmic trading and portfolio construction. Quant firms deploy neural networks and reinforcement learning to identify short-term price movements. Gradient boosting and LSTM models forecast price trends and volatility, enabling adaptive trading strategies. Cloud infrastructure facilitates low latency back testing and deployment of models across global markets. Portfolio optimization uses ML to balance risk and return using historical data, transaction costs, and risk constraints. Limitations include overfitting to past data and regulatory restrictions on model transparency.

All domains share common technical patterns. Data volume and diversity are managed through cloud storage and parallel processing. Model performance improves with feature richness and diversity, provided regularization is applied. Gradient boosting and neural networks excel at structured tasks, while LSTMs and Transformers excel at sequential and NLP tasks. Ensemble approaches combining model types offer strong results, tradeoffs between accuracy and interpretability influence model selection. Explainability tools are embedded within cloud ML pipelines. Real-time applications require low-latency architecture using stream processing and edge computing. Batch processing suffices for non-critical applications. Federated learning supports collaborative model development across institutions. Evaluation remains inconsistent due to proprietary datasets and varying metrics. Robustness against adversarial data and integration of domain expertise remain ongoing challenges. Cloud infrastructure supports hybrid and human-in-the-loop systems. Simpler models may suffice where cost-effectiveness is a factor.

5. Conclusions and Future Work

Cloud-based ML has transformed financial analytics by enabling scalable, real-time insights. From 2021 to 2025, cloud infrastructure empowered fraud detection, credit scoring, and customer personalization through elastic computing and distributed training. Despite broad adoption, ongoing concerns about privacy, regulatory compliance, and model transparency persist.

Recent advances in deep learning, ensemble methods, and hybrid models show that integrating diverse algorithms and data sources yields stronger outcomes. The rise of explainable AI (XAI) and fairness metrics reflects increasing regulatory scrutiny, reinforcing the need for interpretable and accountable systems.

Cloud ML platforms now support collaborative decision-making, particularly for smaller firms and cross-institutional analytics. Federated learning and shared fraud detection models show promise but require secure, ethical data governance. These trends mark a broader shift toward evidence-based, data-driven financial operations.

Future work should explore edge-cloud integration for ultra-low latency use cases and adversarial testing to enhance robustness. Federated and privacy-preserving ML methods, such as homomorphic encryption, will be critical. Lightweight models and streaming analytics can improve responsiveness in high-frequency environments. Developing standardized governance frameworks will support fair, reproducible model practices.

Conflicts of Interest

The author declares that there is no conflict of interest regarding the publication of this paper

References

[1] B. Berisha, E. Mëziu, and I. Shabani, ‘Big data analytics in Cloud computing: an overview’, *J. Cloud Comput.*, vol. 11, no. 1, p. 24, Aug. 2022, doi: 10.1186/s13677-022-00301-w.

[2] Z. Naamane, ‘A SYSTEMATIC LITERATURE REVIEW: BENEFITS AND CHALLENGES OF CLOUD-BASED BIG DATA ANALYTICS’, *Issues Inf. Syst.*, 2023, doi: 10.48009/1_iis_2023_125.

[3] E. J. Adwan and B. A. Alsaeed, ‘Cloud Computing Adoption in the Financial Banking Sector- A Systematic Literature Review (2011-2021)’, *Int. J. Adv. Sci. Comput. Eng.*, vol. 4, no. 1, pp. 48–55, Apr. 2022, doi: 10.62527/ijasce.4.1.73.

[4] ‘The Financial Services Sector’s Adoption of Cloud Services’.

[5] D. B. Vuković, S. Dekpo-Adza, and S. Matović, 'AI integration in financial services: a systematic review of trends and regulatory challenges', *Humanit. Soc. Sci. Commun.*, vol. 12, no. 1, pp. 1–29, Apr. 2025, doi: 10.1057/s41599-025-04850-8.

[6] D. Hoang and K. Wiegratz, 'Machine Learning Methods in Finance: Recent Applications and Prospects'.

[7] N. Prasad, 'Integration of Cloud Computing, Artificial Intelligence, and Machine Learning for Enhanced Data Analytics', *Int. J. Intell. Syst. Appl. Eng.*, vol. 12, no. 22s, Art. no. 22s, Jul. 2024.

[8] D. Mhlanga, 'The role of big data in financial technology toward financial inclusion', *Front. Big Data*, vol. 7, May 2024, doi: 10.3389/fdata.2024.1184444.

[9] A. Garad, H. A. Riyadh, A. M. Al-Ansi, R. Kusumawati, and M. A. Jahid, 'An Overview of Fintech: Opportunities, Challenges and Potential Development', in *From Digital Disruption to Dominance*, M. Shehadeh and K. Hussainey, Eds., Emerald Publishing Limited, 2025, pp. 45–73. doi: 10.1108/978-1-83549-608-420251002.

[10] H. Rehan, 'Modernizing Financial Markets with AI and Cloud Computing: Enhancing Efficiency, Precision, and Security Across Stocks, Crypto, Bonds, and Government Securities', vol. 10, pp. 302–318, Jun. 2024.

[11] S. M. S and M. Karumudi, 'Efficient Workload Portability and Optimized Resource Utilization using Containerization in a Multi-Cloud Environment', in *2024 5th International Conference on Data Intelligence and Cognitive Informatics (ICDICI)*, Nov. 2024, pp. 823–828. doi: 10.1109/ICDICI62993.2024.10810796.

[12] A. Lakkadwala and P. Lakkadwala, 'Accelerating Cloud Deployment Through Containerization Technologies', in *2024 International Conference on Advances in Computing Research on Science Engineering and Technology (ACROSET)*, Sep. 2024, pp. 1–9. doi: 10.1109/ACROSET62108.2024.10743855.

[13] B. Kola, J. Ajayi, and T. Adewale, 'Federated Learning for Privacy-Preserving AI in Sustainable Financial Systems', Jul. 2023.

[14] Q. Zhang, C. Xin, and H. Wu, 'Privacy-Preserving Deep Learning Based on Multiparty Secure Computation: A Survey', *IEEE Internet Things J.*, vol. 8, no. 13, pp. 10412–10429, Jul. 2021, doi: 10.1109/JIOT.2021.3058638.

[15] S. Zhang *et al.*, 'Practical Adoption of Cloud Computing in Power Systems—Drivers, Challenges, Guidance, and Real-World Use Cases', *IEEE Trans. Smart Grid*, vol. 13, no. 3, pp. 2390–2411, May 2022, doi: 10.1109/TSG.2022.3148978.

[16] B. kumar Gaddam, 'Edge Computing: Revolutionizing Real-Time Financial Analytics through Low-Latency Processing', *Int. J. Sci. Res. Comput. Sci. Eng. Inf. Technol.*, vol. 10, no. 6, Art. no. 6, Nov. 2024, doi: 10.32628/CSEIT241061143.

[17] A. Munusamy *et al.*, 'Service Deployment Strategy for Predictive Analysis of FinTech IoT Applications in Edge Networks', *IEEE Internet Things J.*, vol. 10, no. 3, pp. 2131–2140, Feb. 2023, doi: 10.1109/JIOT.2021.3078148.

[18] B. P. Sharma, 'Assessing the Security Implications of Cloud Migration: A Risk Analysis Framework for Protecting Sensitive Data in Multi-Tenant Environments', *Adv. Theor. Comput. Algorithmic Found. Emerg. Paradig.*, vol. 15, no. 3, Art. no. 3, Mar. 2025.

[19] M. Williams, M. F. Yussuf, and A. O. Olukoya, 'MACHINE LEARNING FOR PROACTIVE CYBERSECURITY RISK ANALYSIS AND FRAUD PREVENTION IN DIGITAL FINANCE ECOSYSTEMS', vol. 05, no. 12.

[20] V. Bieger, 'A decision support framework for multi-cloud service composition'.

[21] D. Kreuzberger, N. Kühl, and S. Hirschl, 'Machine Learning Operations (MLOps): Overview, Definition, and Architecture', *IEEE Access*, vol. 11, pp. 31866–31879, 2023, doi: 10.1109/ACCESS.2023.3262138.

[22] J. Kumar Roy and L. Vasa, 'Transforming credit risk assessment: A systematic review of AI and machine learning applications', *J. Infrastruct. Policy Dev.*, vol. 9, p. 9652, Jan. 2025, doi: 10.24294/jipd9652.

[23] C. Zhang, N. N. A. Sjarif, and R. Ibrahim, 'Deep learning models for price forecasting of financial time series: A review of recent advancements: 2020–2022', *WIREs Data Min. Knowl. Discov.*, vol. 14, no. 1, p. e1519, 2024, doi: 10.1002/widm.1519.

[24] L. Hernandez Aros, L. X. Bustamante Molano, F. Gutierrez-Portela, J. J. Moreno Hernandez, and M. S. Rodríguez Barrero, 'Financial fraud detection through the application of machine learning techniques: a literature review', *Humanit. Soc. Sci. Commun.*, vol. 11, no. 1, pp. 1–22, Sep. 2024, doi: 10.1057/s41599-024-03606-0.

[25] G. Cabanes, Y. Bennani, and N. Grozavu, *Unsupervised Learning for Analyzing the Dynamic Behavior of Online Banking Fraud*. 2013. doi: 10.1109/ICDMW.2013.109.

[26] A. Islam, 'DATA GOVERNANCE AND COMPLIANCE IN CLOUD-BASED BIG DATA ANALYTICS: A DATABASE-CENTRIC REVIEW', *Acad. J. Sci. Technol. Eng. Math. Educ.*, vol. 1, pp. 53–71, Oct. 2024, doi: 10.69593/ajieet.v1i01.122.

[27] N. Provatas, I. Konstantinou, and N. Koziris, 'A Survey on Parameter Server Architecture: Approaches for Optimizing Distributed Centralized Learning', *IEEE Access*, vol. 13, pp. 30993–31015, 2025, doi: 10.1109/ACCESS.2025.3535085.

[28] K. Venigandla and N. Vemuri, 'RPA and AI-Driven Predictive Analytics in Banking for Fraud Detection', *Tuijin JishuJournal Propuls. Technol.*, vol. 43, pp. 356–367, Jan. 2022.

[29] M. Srokosz, A. Bobyk, B. Ksiezopolski, and M. Wydra, 'Machine-Learning-Based Scoring System for Antifraud CISIRTs in Banking Environment', *Electronics*, vol. 12, no. 1, Art. no. 1, Jan. 2023, doi: 10.3390/electronics12010251.

[30] A. Ghimire, 'Harnessing Big Data with AI-Driven BI Systems for Real-Time Fraud Detection in the U.S. Banking Sector', *BULLET J. Multidisiplin Ilmu*, vol. 3, no. 6, Art. no. 6, Dec. 2024.

[31] V. L. Heß and B. Damásio, 'Machine learning in banking risk management: Mapping a decade of evolution', *Int. J. Inf. Manag. Data Insights*, vol. 5, no. 1, p. 100324, Jun. 2025, doi: 10.1016/j.jjimei.2025.100324.