Power System Technology
ISSN:1000-3673

Received: 16-11-2025 *Revised: 05-12-2025* *Accepted: 05-01-2026*

Intelligent Data Quality Management Frameworks for AI-Driven Financial Decision Systems

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Abstract: The study analyses smart data quality management models of the AI-based financial decision-making frameworks, overcoming the essential drawbacks of the traditional, manual ones. By considering secondary mixed process, the investigation also summarises the current literature, empirical evidence, and actual case studies to assess the use of AI-based data quality control, data governance, and scalability structures to improve the quality of decisions. The key trends that have been discovered include time-consuming, unstable, and imprecise traditional practice, but AI-moderated automation increases the detection of anomalies by up to 90%, compliance, and real-time financial decision-making. JP Morgan and Capital One Case Evidence Case studies in both financial institutions affirm that the current deep data quality paradigms, managed lifecycle, and embedded in data, are necessary to support trustworthy and sustainable AI-based financial decision-making.

Index Terms: “AI-driven Decision-making”, Automated finance, “Quality management of data”, Economic decision systems, Governance of dataset, “intelligent system”, “scalable architectures”.

Power System Technology
ISSN:1000-3673
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I. INTRODUCTION

A. Background

The financial sector is increasingly using Artificial Intelligence (AI) to aid in important decision-making activities like credit scoring, fraud detection, risk management and algorithmic trading. The AI is simplifying management across the financial domain [1]. As much as AI models have better analytical and predictive models, the success of the models is, by nature, limited by data quality [2]. The problems of data incompleteness, incongruence, and latency may tangibly affect the quality of model performances. Hence, data quality management has become a necessary requirement for reliable and successful use of AI in financial systems.

B. Overview of the Study

This research reviews the data quality management frameworks that are to be used in intelligent financial decision systems that operate with AI. Machine learning can detect the anomalies and enhance the consistencies of data [3]. The study is focusing on higher technologies, such as machine learning, that can be incorporated into data quality procedures to make sure that it is accurate, consistent and compliant with regulations. The research discusses the current data quality issues and problems encountered in financial settings. The smart structures benefiting and enhancing the quality of data throughout the AI lifecycle is being examined.

C. Problem Statement

A large section of financial institutions still considers the traditional rule-based, data quality methods, which are mostly manual and inflexible. These processes have difficulty maintaining the integrity and consistency of contemporary financial data [4]. They can frequently fail to identify usually intricate quality challenges or unusual patterns. This leads to the risk of increased fraud cases and non-compliance with regulations. The adoption of smart, responsive data management models that are aligned with the AI-driven financial systems is a significant issue.

D. Aims and Objectives

The aim of this study is to look at the intelligent data quality management frameworks that could be used to support reliable AI-driven financial decision systems. The specific objectives are 1) To determine crucial data quality issues in AI applications for the financial decision-making process. 2) To critically examine how intelligent techniques can be used to automate data quality management and enhance it. 3) To assess the key elements of resolving effective data quality frameworks of AI-driven financial systems.

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E. Scope and Significance

This research is limited to the area of data quality management in the area of AI-based financial decision systems in the banking and financial services sector. The research holds importance in that it adds to both scholarly and practical knowledge of the use of smart data quality architectures to eliminate risks and enhance the accuracy of decision-making. The findings offer understanding of how to create effective databases in order to sustain and trustworthy AI application throughout the financial industry.

II. LITERATURE REVIEW

A. Common threats in AI-enabled data management systems in making financial decisions

The quality of data is a crucial limiting factor to the efficiency of AI-based systems used to make financial decisions. As shown by Pillai (2023), the AI methods of neural networks, NLP-based sentiment analysis, and algorithmic trading prove to be extremely effective in predicting the accuracy and timing of the market. Although their effectiveness strongly depends on the integrity of the data, its timeliness, and consistency [5]. Unstructured text, streams of data, and heterogeneous data have a negative effect on the creation of rational and trusted error reduction resources through a multifaceted financial ecosystem. These organisations are exposed to greater risks of noise, incompleteness, and bias, which can be propagated by means of the AI models and hubs affecting the quality of the decisions that they make. Another study also states that even the supranational data quality methods by manual means are not sufficient to meet such challenges, since they cannot be used to scale or respond to changing data pipelines [6]. What they find is the endemic problems of lack of values, discrepancies, and aberrations that directly have impacts on the accuracy of analytics and governance in AI-enabled systems. Despite the enhanced detection provided by AI-powered monitoring, the literature reveals that data quality lapses cannot be resolved yet, which is a major weakness of financial analytics.

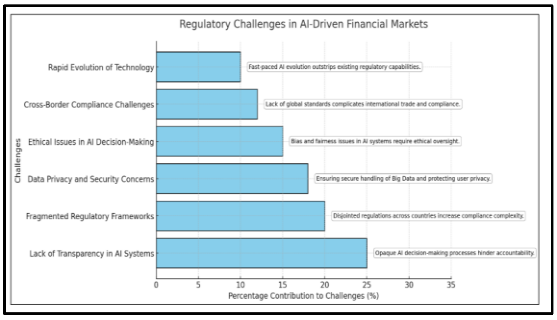

Figure 1: AI in Financial Markets Regulatory Challenges

[7]

Such data quality issues, Ekundayo (2024) puts these concerns in a wider regulatory and economic framework. They highlight that these invisible AI decision-making, fragmented

Power System Technology
ISSN:1000-3673
Received: 16-11-2025 Revised: 05-12-2025 Accepted: 05-01-2026

regulations, and privacy perils join the impact of poor data quality [7]. Absence of transparency and divided structures aggravates the risks of compliance and accountability, as shown in Figure 1 [7]. Overall, the given studies can prove that a gap related to managing data quality proactively in the lifecycle of AI continues to exist. This directly coincides with the interest of the current study, which focused on intelligent and adaptive data quality management frameworks of financial decision systems.

B. Smart Methods of Automated Data Quality Management of Financial Systems

The current evidence-based literature points strongly to the fact that intelligent methods serve as the core point of the effective solution to the long-standing data quality constraints in AI-based financial systems. Verma (2024) claims that automatic data pipelines, perpetuated checking, and AI-valuing writings are some of the brilliant practices of data engineering that cannot be bypassed to achieve exactness, uniformity, and on-scaled financial AI practices. This conforms to Figure 2, which puts forth the role of intelligent automation in dealing with data silos, complexity, and the limitations of legacy systems [8].

Challenge	Solution
Data Silos	Data integration platforms
Complexity of Data	Standardization and automation
Legacy Systems	Modernization and cloud migration

Figure 2: Problems and Resolutions

[8]

Puchakayala (2022) offers a larger analysis perspective where redundancy, inconsistency, and out-of-date data are perceived as the key issues of successful AI and ML modelling. Intelligent data cleansing, anomaly detection, and identification of patterns are pointed out in the literature as the best practices that have a direct effect on enhancing model reliability and trustworthiness [9]. Nevertheless, it mentions numerous AI failures that are caused by the lack of focus on data quality when the model is developed. Ramaliba and Jacobs (2024) further this explanation to the banking industry and suggest a research AI-based data quality management model based on governance, regulation, and technology. Their results point out that the application of intelligent methods can automate quality assurance, but the regulatory and organisational preparedness is not balanced [10]. Overall, considering these articles' key findings, the need for a smart and adaptive quality management is clear. This directly underpins the current research interest in the automated, scalable solutions to AI-driven financial decision systems.

C. Structures and Systems to Efficient Data Quality Management in AI-driven Financial Decisions

The current literature is moving toward the view that to manage the quality of data in AI-powered financial systems well, one needs comprehensive, smart structures, but not discrete

Power System Technology
ISSN:1000-3673
Received: 16-11-2025 Revised: 05-12-2025 Accepted: 05-01-2026

technical measures. The authors present AI-powered data quality oversight engineering, suspicious of the data, customised preceding, and a bi-sectional learning of the data pipeline to high-volume patterns [11]. Albeit being conceptually sound, the framework is highly abstract, which points to the lack of bridging between architectural design and its feasible application in regulated financial settings. Moreover, data quality can be operationalised through AI-based governance structures that will automate the data classification, compliance enforcement, and discovery of anomalies by implementing multi-layered structures [12]. According to simulation outcomes, the indicators of security and compliance are observably improved, which supports the thesis that the data quality framework in financial systems should be closely linked to the governance and compliance mechanisms. Adenuga *et al.* (2024) also expand the reasoning by putting the issue of data quality in the context of scalable and cloud-native enterprise architecture. They indicate that to ensure data reliability and interoperability in AI-based decision systems, intelligent data lakes, real-time pipelines, and governance-by-design are needed [13]. Altogether, these studies substantiate the current research objective by proving the necessity of holistic, flexible data quality systems that combine architecture, governance, and intelligence along the AI lifetime in the context of financial decision-making.

III. RESEARCH METHODOLOGY

A. Research Design

This research is applying explanatory research design to analyse intelligent types of data quality management systems that facilitate AI-based financial decision systems. This research design is suitable for studying a complicated technical phenomenon that includes interactions between data management policies, artificial intelligence models, and decision-making in the financial field. The explanatory research is vital for establishing the cause-and-effect relationships between the different variables [14]. The explanatory design is helping the study to analyse the impact of intelligent data quality mechanisms in enhancing reliability, accuracy, and transparency of AI-driven financial decisions. This design is enabling the study to equate the data quality practises with the operational and regulatory issues that financial institutions encounter.

B. Data Collection

The research data is being gathered using secondary sources such as journals, industry reports, and regulatory documents of the financial institutions and technology providers. The technical reports, framework descriptions, and accessible case studies are sources of evidence of the practical applications of intelligent data quality management to AI-based financial systems. The qualitative data gives a perspective on framework structures, governance models, and how smart automation can be utilised to control the quality of data. The quantitative data is being obtained from published statistics, performance indicators and empirical findings reported by

Power System Technology
ISSN:1000-3673
Received: 16-11-2025 Revised: 05-12-2025 Accepted: 05-01-2026

previous studies. The numeric data depicts the benefit of improving data quality on AI model accuracy, robustness and reliability of its decisions. The qualitative and quantitative evidence is enabling the study to create an inclusive insight into how intelligent data quality management models may benefit effective and reliable AI-infused financial decision systems.

C. Evaluation Metrics

The efficacy of smart data quality management models is determined through the application of a variety of qualitative and quantitative instruments. The accuracy, completeness, and consistency of financial data utilised in AI models are some of the major evaluation metrics being used. The evaluation metrics are being used for quantifying the indicators vital for understanding data quality [15]. In terms of AI performance, it can be stated that model accuracy, precision, recall, and data drift invariance are measured to evaluate the impacts of data quality enhancements. The operational measures, such as the decrease of manual data cleansing, data anomaly detection time, and compliance preparedness, are being evaluated. The study is using these evaluation metrics to realise the overall impact of intelligent data quality models on AI-based financial decisions.

D. Case Study Examples

Case Study 1: JP Morgan using data quality management

The use of data quality management systems can be noted in the context of JP Morgan making use of an application called Fusion. The application provides end-to-end data management. There is reporting carried out across the investment cycle. The platform combines and integrates data from multiple sources within a single data model to eliminate any chances of inconsistencies [16]. The bank is able to gather timely insights and learning from the data models, owing to the quality management framework.

Case Study 2: Capital One, focusing on data quality management

Capital One is focusing on effective data quality management practices for achieving crucial results. The company is ensuring critical governance techniques to have good consistency of maintenance of data across the modules. The company is making use of reusable and modular data management units, which is leading to enforcing the standards from early on [17]. The company is using machine learning techniques for performing consistent quality checks and identifying sensitive data.

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ISSN:1000-3673
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IV. FINDINGS

A. Data presentation

Figure 3: Weaknesses of the Traditional Approach

[6]

The given figure demonstrates the severe ineffectiveness of conventional data quality management, which directly explains the necessity of intelligent structures in AI-driven finance. The limitations identified in the data are "Time-Consuming Processes" (significantly 90%) and "Manual Error Detection" (85%). Financial decision systems indicate that the need to process these numbers manually does not allow for real-time processing to identify fraud cases. Moreover, the prevalence of "Inconsistency of Data Validation" (80%) is a sign of systemic risk when standard rules cannot guarantee the data integrity on which the accurate training of AI models can be based [6].

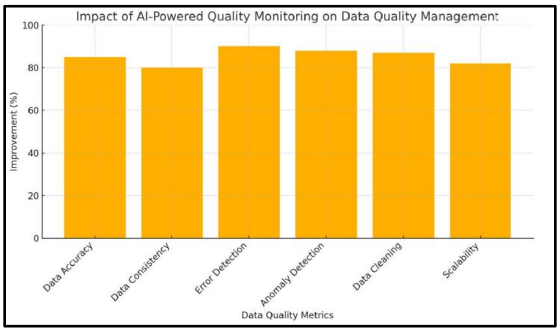

Figure 4: The Effects of AI-Powered Quality Monitoring

[6]

The number shows a substantial increase in performance in all data quality indicators in case of using AI-driven monitoring. The most notable results show that it has increased its ability to detect "Anomalies and errors" by 90% and 88%, respectively [6]. These statistics are important to this research, as these numbers show how smart systems lessen the danger of fraud

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and non-adherence by robotizing the detection of sophisticated trends that human systems can easily ignore.

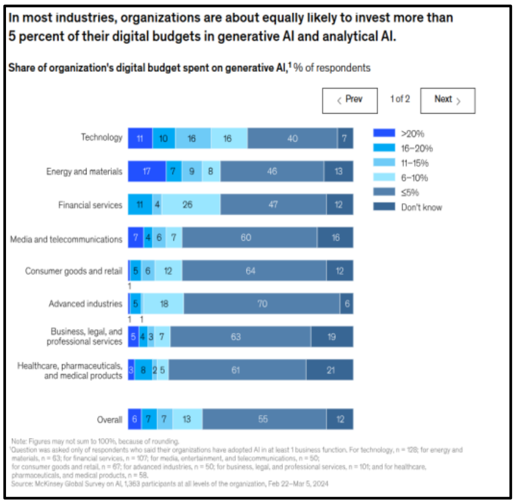

Figure 5: The Implication of AI-Powered Quality Monitoring

[18]

The amount, which has been taken from the McKinsey 2024 "Technologies Trends Outlook", displays a significant shift in digital budgets towards "AI Foundational Services" and "AI-First Vertical Solutions". In this study, it means that this trend is shifting toward abandoning the traditional services which are being outsourced by financial institutions (which will essentially drop by 10%) to more specialised, modular architecture. This has been mainly influenced by the requirement of a robust and smart data quality layer to maintain intricate AI-based financial decision-making [18].

B. Findings

The reported results all indicate that the conventional approaches to data quality are simply ineffective in AI-based financial decision systems, as they are manual, time-consuming, and inconsistent [6]. It has been proven that quality monitoring based on AI is much more effective in the detection of errors and anomalies, which directly increases the reliability of the model and regulatory efficiency. In addition, a strategic change in financial institutions' digital investment to AI-first architectures. This justifies the research aim and attests to the increasing need to establish intelligent, scalable data quality management systems to facilitate reliable and sustainable AI-based financial decision making.

Power System Technology
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C. Case study outcomes

Case Study	Key Outcomes	Relevance to Present Research
JP Morgan (Fusion Platform)	Coherent multi-source data, with even fewer areas of conflict, allowed receiving opportunities in a timely manner throughout the lifecycle of an investment [16].	Illustrates that the intelligence and reliability of end-to-end, sensitive AI-enabled finance is achieved with the help of intelligent data quality structures.
Capital One	Powerful governance, data unit modularity, quality checks by means of ML, and sensitive data recognition [17].	Illustrates the importance of AI-assisted automated data quality management based on the regulations and scalability requirements.

Table 1: Case Study Analysis

(Source: Self-developed)

The two case studies are empirical evidence of the objective of the research since they show that smart, automated data quality frameworks enhance consistency, governance, and reliable decisions in practice banking environments. These two instances confirm the fact that the AI-based financial systems are known to need the embedded data quality architectures to maintain scalable, compliant, and reliable decision-making.

D. Comparative analysis

Authors	Focus	Key Findings	Gaps
[5]	AI in big data analytics for financial decisions	AI enhances the accuracy of the predictions, sentiment analysis, and the effectiveness of algorithmic trading.	Poor emphasis on systematic data quality governance as well as life cycle controls.
[6]	AI-powered data quality monitoring	Anomaly detection and automation are useful in improving governance, scalability, and accuracy.	Sector-based regulatory integration by Lacks.

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[7]	Economic and regulatory implications of AI finance	Brings out transparency, governance, and systemic risk.	Fails to put forward specific data quality structures.
[8]	Data engineering and data quality in finance	This is because strong pipelines and standards form essential success factors in AI.	A lack of empirical validation.
[9]	Data quality best practices for ML/AI	Determines data flaws and data cleansing.	Weak real-time financial systems.
[10]	AI-driven data quality in banking	Conceptual framework based on governance.	Limited generalisability, which is context-specific.
[11]	AI-driven data quality architecture	Suggests learning monitoring, which is adaptive.	Theory, no support for implementation.
[12]	AI governance & scalable architectures	AI enhances security, interoperability, and compliance.	The integration with the financial decision work procedure is under stress.
[13]	Scalable and secure data infrastructure for AI	Cloud-native architectures enable reliable, real-time AI decisions	Data quality management is not addressed as a standalone framework

Table 2: Comparative analysis

(Source: Self-developed)

The comparative analysis shows that there is largely agreement that the effectiveness of AI in financial systems of decision-making depends on the quality of information that is well managed. Although current literature proves improvement of automation, governance, and scalable architectures, most are conceptual or of a narrow scope, demonstrating isolated parts. Interestingly, it was observed that there is little work that outlines the integration of intelligent data quality management throughout the entire AI lifecycle, as well as aligns the technical controls with the regulatory and decision-making demands [10; 11; 13]. The gap directly informs the current study that aims to synthesise intelligent, adaptive, and cognizant governance data quality structures for AI-based financial decision systems.

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V. DISCUSSION

A. Interpretation of results

The findings show that smart, AI-based data quality management is much more powerful in terms of accuracy, consistency, and real-time responsiveness as compared to traditional approaches. To enable resilient AI-driven financial decision systems to minimise the operational and compliance risks, efficient automation, governance, and scalable architectures should be considered.

B. Practical Implications

In the case of financial institutions, the implementation of smart data quality systems can synchronise faster fraud identification, enhanced credit, and enhanced tolerance of regulatory requirements. Automated monitoring saves time and manual work, and guarantees reliable data pipelines, which can be trusted in order to run scalable and reliable AI applications.

C. Shortcomings

Although there are undeniable advantages, some difficulties exist, such as the expensive implementation process, the integration of the older system, weak clarity of the regulations, and the issue of data privacy. Also, a good number of them do not have empirical support in real-time financial settings, limiting the externalisable of present results.

D. Recommendations

Financial institutions should invest in the AI-enabled data quality solution integrated in automated monitoring and anomaly detection, and in continuous learning on the AI lifecycle. The alignment of data quality controls with data governance models (e.g., DAMA, the regulatory standards, such as GDPR, Basel III) is critical [19]. Modular cloud-native architectures should be the highest priority of organisations to be scalable and interoperable [20]. Other suggestions that should be applied in the future are regular audits, explainable AI mechanisms, and cross-functional interactions between the data, risk, and compliance teams.

VI. CONCLUSION AND FUTURE WORK

The results of the present study indicate that intelligent data quality management systems act as a key facilitator of credible AI-based financial decision-making. Conventional manual techniques are no longer applicable when authenticated and approved to handle the scale, velocity, and complexity of contemporary financial information. On the other hand, AI empowered monitoring, governance, and scalable structures are effective in their reliability to enhance the accuracy, compliance, and trustworthiness of decisions. The study shows that combined frameworks are necessary to incorporate data quality controls throughout the AI lifecycle. Further research must be directed at the empirical experimentation of hypothesised

Power System Technology
ISSN:1000-3673
Received: 16-11-2025 Revised: 05-12-2025 Accepted: 05-01-2026

frameworks with actual financial implementations, comparative performance measurement, and further research into explainable AI and regulator-congruent data quality automated schemes.

VII. REFERENCE LIST

[1] Becerra-Vicario, R., Salas-Compás, B., Valcarce-Ruiz, L. and Sánchez-Serrano, J.R., 2024. The Impact of Artificial Intelligence in The Financial Sector: Opportunities and Challenges. *International Journal of Business & Management Studies*, *5*(10), pp.33-42.

[2] Ramaliba, T. and Jacobs, L., 2024. Artificial intelligence technology to enhance data quality management practices in the banking industry in South Africa. *South African Journal of Libraries and Information Science*, *90*(2), pp.1-10.

[3] Verma, R., 2024. Building Robust AI Systems in Finance: The Indispensable Role of Data Engineering and Data Quality. *ESP International Journal of Advancements in Computational Technology*, *2*(1), pp.80-89.

[4] Kothandapani, H.P., 2022. Optimizing financial data governance for improved risk management and regulatory reporting in data lakes. *International Journal of Applied Machine Learning and Computational Intelligence*, *12*(4), pp.41-63.

[5] Pillai, V., 2023. Integrating AI-driven techniques in big data analytics: Enhancing decision-making in financial markets. *International Journal of Engineering and Computer Science*, *12*(07), pp.10-18535.

[6] Shah, K.N., Gami, S.J. and Trehan, A., 2024. An intelligent approach to data quality management AI-Powered quality monitoring in analytics. *International Journal of Advanced Research in Science Communication and Technology*, *4*(3), pp.109-119.

[7] Ekundayo, F., 2024. Economic implications of AI-driven financial markets: Challenges and opportunities in big data integration. *International Journal of Science and Research Archive*, *13*(2).

[8] Verma, R., 2024. Building Robust AI Systems in Finance: The Indispensable Role of Data Engineering and Data Quality. *ESP International Journal of Advancements in Computational Technology*, *2*(1), pp.80-89.

[9] Puchakayala, P.R.A., 2022. Data Quality Management for Effective Machine Learning and AI Modelling, Best Practices and Emerging Trends. *International Research Journal of Innovations in Engineering and Technology*.

[10] Ramaliba, T. and Jacobs, L., 2024. Artificial intelligence technology to enhance data quality management practices in the banking industry in South Africa. *South African Journal of Libraries and Information Science*, *90*(2), pp.1-10.

Power System Technology
ISSN:1000-3673
Received: 16-11-2025 Revised: 05-12-2025 Accepted: 05-01-2026

[11] Bangad, N., Jayaram, V., Krishnappa, M.S., Banarse, A.R., Bidkar, D.M., Nagpal, A. and Parlapalli, V., 2024. A Theoretical Framework for AI-driven data quality monitoring in high-volume data environments. *arXiv preprint arXiv:2410.08576*.

[12] Potdar, A., 2024. AI-based big data governance frameworks for secure and compliant data processing. *International Journal of Artificial Intelligence, Data Science, and Machine Learning*, *5*(4), pp.72-80.

[13] Adenuga, T., Ayobami, A.T., Mike-Olisa, U. and Okolo, F.C., 2024. Enabling AI-Driven Decision-Making through Scalable and Secure Data Infrastructure for Enterprise Transformation. *International Journal of Scientific Research in Science, Engineering and Technology*, *11*(3), pp.482-510.

[14] Kahihu, P.K., Wachira, D.M. and Muathe, S.M., 2021. Managing market risk for financial performance: experience from micro finance institutionin Kenya. *Journal of Financial Regulation and Compliance*, *29*(5), pp.561-579.

[15] Makhoul, N., 2022. Review of data quality indicators and metrics, and suggestions for indicators and metrics for structural health monitoring. *Advances in Bridge Engineering*, *3*(1), p.17.

[16] JpMorgan.com, 2024, *The key to effective data management*, Available at: https://www.jpmorgan.com/insights/securities-services/data-solutions/data-access-catalog-mesh [Accessed on: 5th July, 2025]

[17] Forbes.com, 2024, *How Capital One Is Evolving Data Management To Build A Trustworthy, AI-Ready Data Ecosystem*, Available at: https://www.forbes.com/sites/capitalone/2024/07/15/how-capital-one-is-evolving-data-management-to-build-a-trustworthy-ai-ready-data-ecosystem/ [Accessed on: 14th July, 2025]

[18] Mckinsey.com, 2024, *The state of AI in early 2024: Gen AI adoption spikes and starts to generate value,* Available at: https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai-2024, [Accessed on: 19th August 2025]

[19] Kothandapani, H.P., 2022. Optimizing financial data governance for improved risk management and regulatory reporting in data lakes. *International Journal of Applied Machine Learning and Computational Intelligence*, *12*(4), pp.41-63.

[20] Ugwueze, V.U., 2024. Cloud native application development: Best practices and challenges. International Journal of Research Publication and Reviews, 5(12), pp.2399-2412.

Power System Technology
ISSN:1000-3673
Received: 16-11-2025 *Revised: 05-12-2025* *Accepted: 05-01-2026*

[21] Devapathni Yugandhar, M. B., Goli, A. K. R., Goli, S. R., & Chawla, N. (2025, August). Comprehensive Analysis of Challenges in Deploying AI Models in FinTech. In 2025 2nd International Conference on Intelligent Algorithms for Computational Intelligence Systems (IACIS).

[22] Goli, S. R., Deshpande, G., Konda, R., & Goli, A. K. R. (2025, August). Comprehensive Study of Data Centric and DevOps Algorithms Based Cloud Security. In 2025 2nd International Conference on Intelligent Algorithms for Computational Intelligence Systems (IACIS) (pp. 1-5). IEEE.

[23] Chintale, P., & Gupta, G. (2025). Blockchain-Based Authentication Scheme/Framework for Secure Data Sharing. In AI and Blockchain in Smart Grids (pp. 107-126). Auerbach Publications.

[24] Goli, S. R. (2025). Towards Converged MLOps and SRE: Adaptive AI-Driven Reliability Strategies in Cloud Environments. Available at SSRN 5741602.