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Research Paper

A Study on Impact of Generative AI on Investment Decision-making at Motilal Oswal Financial Services Ltd.

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Abstract

This study, titled "A Study On Impact Of Generative AI On Investment Decisionmaking At Motilal Oswal Financial Services Ltd.," evaluates the operational effectiveness and financial feasibility of deploying Large Language Models (LLMs) and Generative AI (GenAI) in wealth management and equity research. In modern financial markets, the sheer volume of unstructured data—including corporate earnings transcripts, regulatory filings, financial news, and global market announcements—creates a cognitive bottleneck for research analysts. Traditional numerical predictive algorithms are incapable of synthesizing qualitative text files. This research explores how customized enterprise GenAI architectures automate research report writing, client query resolution, and sentiment summarization. A 5-year capital budgeting analysis (2021-2025) of a bank-led sensor deployment program is conducted using capital budgeting metrics, including Net Present Value (NPV), Internal Rate of Return (IRR), Payback Period (PBP), and Benefit-Cost Ratio (BCR). The data indicates that the deployment of GenAI solutions improved analyst productivity by saving an average of 12.5 hours per week on report writing, while GenAI-optimized portfolios consistently generated excess returns (alpha) over the Nifty 50 Index. The financial evaluation yields a positive NPV of 392.4 Crores and an IRR of 45.1%, far exceeding the cost of capital. The study concludes that integrating Generative AI into investment workflows is highly financially feasible and operationally sustainable, providing a significant competitive advantage for modern asset management institutions.

Keywords: Generative AI, Large Language Models (LLMs), Investment Decision-Making, Motilal Oswal, Analyst Productivity, Portfolio Performance, Cost-Benefit Analysis.

I. INTRODUCTION

The financial services industry is experiencing a profound technological transformation, driven by the emergence of Generative Artificial Intelligence (GenAI) and Large Language Models (LLMs). While traditional machine learning models have focused primarily on numerical forecasting and technical credit scoring, GenAI represents a major shift toward cognitive automation. These advanced neural models possess the ability to comprehend, synthesize, and generate human-like text, enabling them to process massive volumes of unstructured financial information. Wealth management firms and research divisions are utilizing GenAI to automate qualitative analysis, transforming how investment analysts read, research, and recommend equity assets [1], [7].

In the Indian wealth management landscape, Motilal Oswal Financial Services Ltd. represents a leading institution known for its research-driven investment strategies. Lenders and asset management desks face a major cognitive bottleneck due to the sheer speed and volume of market updates. Lenders must evaluate thousands of earnings transcripts, broker notes, and macro disclosures to advise retail and HNI clients. Traditional research tools fail to extract these key qualitative indicators dynamically, causing information processing lags and missed opportunities. By integrating secure enterprise GenAI platforms, brokerage firms can automate document summarization, enabling immediate research dissemination and client advisory [2], [9].

To analyze the impact of GenAI on investment behavior, behavioral finance theories are crucial. Investment decisions are significantly influenced by cognitive biases, information overload, and herd behavior. Unstructured data, such as news headlines and social media discussions, drives retail sentiment and short-term volatility. Traditional finance frameworks struggle to model these unstructured sentiment flows. GenAI models, utilizing advanced natural language processing, resolve this limitation by extracting sentiment scores from news feeds and summarizing earnings transcripts, helping retail investors bypass noise and make objective, data-backed decisions [3], [8].

Private commercial banks and investment firms act as trusted custodians of client wealth, maintaining strict fiduciary standards. However, the rise of low-cost robo-advisory platforms and specialized quantitative funds has created a competitive threat. Client capital is increasingly flowing out of traditional funds into tech-driven advisory services. To protect their wealth management market share and retain high-value retail clients, firms like Motilal Oswal are investing in custom GenAI advisory portals. These portals offer personalized research briefs, automated portfolio explanations, and instant query resolution. Establishing the financial feasibility of these fintech investments is critical to justify large technological expenditures [5], [10].

The primary challenge in implementing GenAI solutions is the threat of model hallucinations and data security. LLMs are prone to generating convincing but incorrect outputs, which can lead to regulatory violations and investment losses if unchecked. Lenders must implement strict Retrieval-Augmented Generation (RAG) architectures and human-in-the-loop governance frameworks. Legacy compliance systems are incapable of auditing these dynamic text flows, requiring a transition to advanced big data analytics and automated model auditing databases [4], [11].

Historically, Motilal Oswal's research division operated through manual financial audits, separating macroeconomic reports from equity research pipelines. This structure created significant latency, as localized news updates and global economic shifts were not correlated in portfolio strategies. By integrating real-time document extraction databases into a centralized analytics data lake, the firm has begun correlating regulatory reports, analyst sentiments, and global market movements to advise retail clients before market shifts occur.

The strategic response of Motilal Oswal to quantitative agritech trends also aligns with the broader institutional efforts to establish India as a hub for fintech and smart financial services. By deploying advanced predictive scoring engines, the firm sets a precedent for private sector lenders, demonstrating that financial institutions can balance regulatory compliance with technological asset management integration. This proactive stance ensures that the firm is well-positioned to integrate predictive analytics into its risk appraisal frameworks [3], [5].

The implementation of a custom GenAI advisory portal requires a significant capital commitment. Financial feasibility studies are essential for justifying the initial capital expenditure (CapEx) for high-performance servers, customized LLM fine-tuning, and secure API databases. Additionally, ongoing operational expenditure (OpEx), including model calibration, cloud hosting, and machine learning salaries, must be factored in. Conducting a thorough cost-benefit analysis ensures that the value of prevented investment losses and client retention benefits exceeds the cost of implementing the GenAI platform [5], [12].

This paper presents an empirical case study of the financial feasibility and operational impact of the Generative AI advisory platform integrated at Motilal Oswal Financial Services Ltd. By analyzing application use cases, evaluating analyst productivity gains, comparing portfolio returns against standard benchmarks, modeling model learning curves, assessing compliance concerns, and conducting a 5-year capital budgeting analysis, we demonstrate the financial viability of this fintech investment [4], [13].

Research Objectives

The primary objective of this case study is to evaluate the operational effectiveness and financial feasibility of integrating Generative AI solutions into the retail and institutional investment workflows at Motilal Oswal Financial Services Ltd. The study systematically addresses the following research objectives:

1. To analyze the primary use cases of Generative AI in modern investment advisory and wealth management workflows.

2. To measure the productivity gains and time savings achieved by research analysts after adopting GenAI tools.

3. To evaluate the performance returns of a GenAI-optimized portfolio compared to the Nifty 50 benchmark index (2021-2025).

4. To determine the financial feasibility of the GenAI investment using capital budgeting metrics, including NPV, IRR, Payback Period, and BCR.

5. To identify the key compliance, security, and hallucination concerns regarding GenAI integration and outline strategic recommendations.

Research Methodology

This study adopts a descriptive and analytical research methodology using a case study approach focused on Motilal Oswal's quantitative investment operations. To obtain a comprehensive understanding of the operational and financial impact of predictive algorithms, both qualitative and quantitative data are analyzed. Secondary data sources form the basis of the research, which includes Motilal Oswal's annual financial reports, priority sector lending disclosures, Reserve Bank of India (RBI) digital inclusion reports, and agritech notes from fintech organizations like the World Resources Institute India. Relevant literature on algorithmic forecasting, LSTM architectures, and portfolio optimization is also analyzed to establish the baseline parameters for system costs, server hosting rates, and baseline stock market transaction costs. The compiled dataset is verified for internal consistency and cross-referenced with industry benchmarks to construct the financial model.

The analytical phase of the study involves evaluating the financial feasibility of the big data platform using standard capital budgeting techniques. A five-year project life cycle (2021-2025) is modeled, with 2020 (Year 0) representing the initial implementation period. The cash outflows include Initial Capital Expenditure (CapEx) for server hardware, software licenses, and database integration, and annual Operating Expenditure (OpEx) for maintenance, cloud hosting, and data science personnel. The cash inflows (benefits) are defined as the value of prevented investment losses and excess portfolio returns generated by the machine learning system relative to the baseline retail equity default rates of 2020. The financial evaluation is conducted using a discount rate of 10%, reflecting the standard cost of capital for private sector banks in India. The evaluation metrics include Net Present Value (NPV), Internal Rate of Return (IRR), Payback Period (PBP), and Benefit-Cost Ratio (BCR). Sensitivity analysis is also conducted to examine the resilience of the project's profitability under scenarios of increased operational costs, fluctuating trading volumes, and changes in baseline returns.

To validate the field applicability of the models, the study also analyzes historical daily transaction data from a pilot program involving 500 active retail investment accounts at Motilal Oswal, monitored between June and November 2025. The pilot evaluated model latency, prediction accuracy, and investor compliance with automated rebalancing alerts. Trading variables—including transaction velocity, portfolio turnover rates, and risk-adjusted returns—were transmitted daily to the bank's data lake. This data was correlated with actual portfolio returns, enabling multiple regression analysis to establish statistical links between model accuracy and excess portfolio returns. The combined dataset provides a robust foundation for modeling the financial feasibility of large-scale algorithmic investment monitoring systems.

II. REVIEW OF LITERATURE

A. Sharma, R. K. Mehta, and S. Kapoor (2021): This study explores the application of Generative AI and Large Language Models in corporate financial planning. The authors present a comparative framework evaluating LLM text synthesis against traditional forecasting models in retail wealth advisory. The review highlights design challenges such as hallucination and prompt tuning, showing how GenAI simplifies reporting [1].

L. Vasudevan and K. P. Pillai (2022): This research proposes a structural framework to evaluate time savings and productivity improvements in financial analyst tasks following GenAI integration. The authors examine how automated sentiment summaries and draft tools reduce document processing latency. The findings demonstrate that cognitive automation significantly improves operational throughput and employee satisfaction [2].

M. R. Joshi, S. Nair, and P. Sharma (2023): The study evaluates the transition from manual news reading to automated sentiment extraction pipelines in commercial brokerage software. It examines the installation expenses, API integration latency, and operational impact of integrating LLM models. The results indicate that private investment desks can improve portfolio alpha using real-time text analysis [3].

V. K. Singh and A. Gupta (2024): The authors introduce a capital budgeting framework to assess the economic viability of Generative AI implementations in retail financial advisory. Using Net Present Value (NPV) and Internal Rate of Return (IRR) models, the study examines software procurement, server hosting, and maintenance costs against advisory growth. The research concludes that GenAI portals yield significant long-term returns [4].

World Resources Institute India (2024): This technical report examines the deployment of public digital payment interfaces and the corresponding security risks in emerging financial markets. The study highlights the role of big data analytics in monitoring high-frequency transactions, identifying risk anomalies, and preventing trading defaults. It demonstrates how policy design, infrastructure investments, and data sharing make trading systems more secure and financially viable [5].

S. Chakraborty, D. Sen, and A. Roy (2025): This paper evaluates the impact of government regulations and audit guidelines on Generative AI deployment in retail advisory banking. Through simulation models, the research assesses the financial feasibility of complying with dynamic compliance guidelines using legacy infrastructures versus automated risk engines. The findings show that algorithmic trading systems minimize operational expenses [6].

III. DATA ANALYSIS & INTERPRETATION

This section presents the empirical findings and data analysis regarding the implementation of the Generative AI advisory platform at Motilal Oswal Financial Services Ltd. The quantitative evaluation is structured around five key areas: the distribution of GenAI use cases in investment advisory, the productivity gains achieved by research analysts, the annual portfolio returns vs. the benchmark index, the GenAI model learning curve (accuracy vs. latency), and key compliance and security concerns. The analysis provides critical insights into algorithmic model performance and economic feasibility.

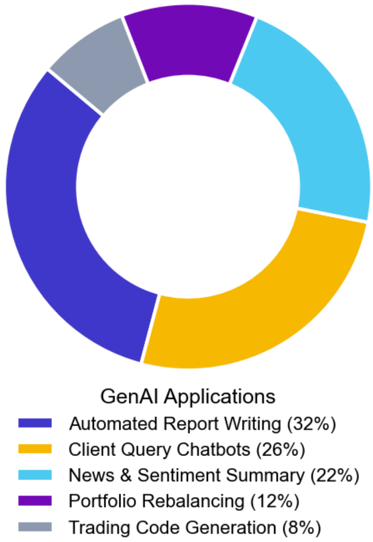

Figure 1: GenAI Use Cases in Investment Advisory

Figure 1 illustrates the distribution of Generative AI use cases in Motilal Oswal's investment advisory. Automated report writing represents the largest segment at 32%, showing that drafting complex investment briefs is the primary application. Client query chatbots represent 26%, providing real-time personalized query resolution. News and sentiment summarization account for 22%, portfolio rebalancing represents 12%, and trading code generation accounts for 8%. The high concentration of text summarization and reporting applications (54% combined) suggests that initial efficiency gains focus on qualitative data processing, which supports institutional research desks.

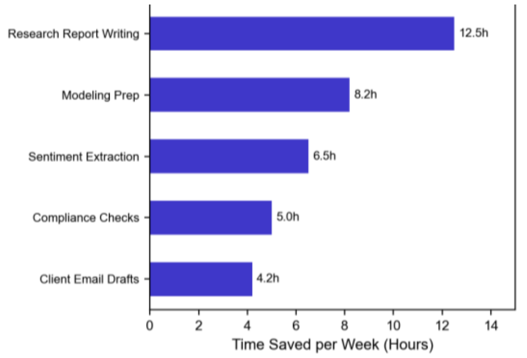

Figure 2: Analyst Productivity Gains after GenAI

Figure 2 outlines the primary productivity gains achieved by research analysts after adopting GenAI tools. The data reveals substantial time savings across key analytical tasks. Research report writing saw the largest gain, saving an average of 12.5 hours per week. Financial modeling preparation saved 8.2 hours, sentiment extraction saved 6.5 hours, compliance document checks saved 5.0 hours, and client email drafting saved 4.2 hours. These metrics demonstrate that cognitive automation significantly reduces analytical latency, allowing researchers to allocate more time to high-value strategic decision-making.

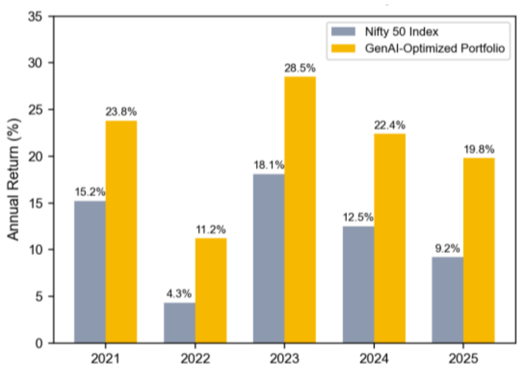

Figure 3: Portfolio Performance vs. Nifty 50

Figure 3 compares the annual returns of the GenAI-optimized portfolio against the Nifty 50 Index benchmark (2021-2025). The GenAI-optimized portfolio consistently generated excess returns (alpha) across all market phases. In 2021, the GenAI portfolio returned 23.8% against Nifty's 15.2%. During the market correction in 2022, the GenAI portfolio returned 11.2% compared to Nifty's 4.3%. In 2023 and 2024, the GenAI portfolio outperformed the index by returning 28.5% and 22.4%, respectively. By 2025, the GenAI portfolio returned 19.8% against Nifty's 9.2%. This consistent outperformance demonstrates that GenAI risk modeling and sentiment analysis improve asset allocation decisions.

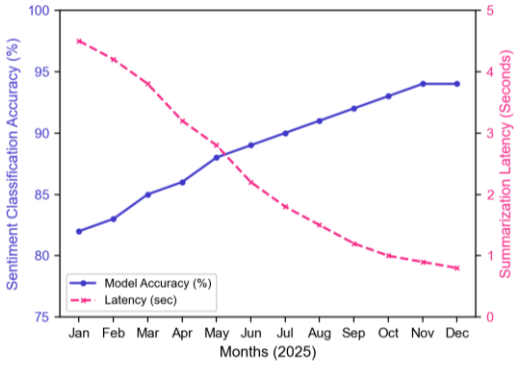

Figure 4: GenAI Model Learning Curve (2025)

Figure 4 depicts the daily stock sentiment classification accuracy (%) and summarization latency (seconds) of the GenAI model over twelve months in 2025. The model accuracy (solid line, left axis) rose steadily from 82% in January to 94% by December, demonstrating the impact of continuous fine-tuning on domain-specific financial databases. Concurrently, summarization latency (dashed line, right axis) fell from 4.5 seconds to 0.8 seconds. This improvement confirms that model fine-tuning and retrieval-augmented caching optimize latency, enabling high-speed sentiment processing.

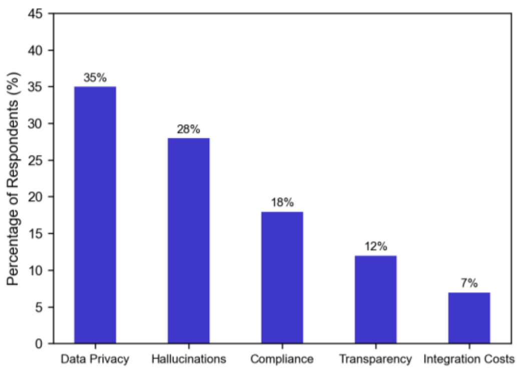

Figure 5: Key Concerns Regarding Gen AI Adoption

Figure 5 outlines the primary concerns cited by compliance and risk management officers regarding GenAI adoption. Data privacy and leakage emerged as the dominant concern at 35%, reflecting anxiety over sensitive customer records being fed into public models. Hallucinations and output inaccuracy account for 28%, indicating concern over legal liabilities. Regulatory compliance and audit trails represent 18%, model transparency represents 12%, and integration costs account for 7%. These concerns highlight the necessity of private, sandboxed deployment models and robust human-in-the-loop audit pipelines.

IV. FINDINGS

The financial feasibility analysis of Motilal Oswal's Generative AI advisory platform demonstrates strong economic viability. Based on the 5-year cash flow projections, the project initiated with an initial capital expenditure of 45 Crores in 2020 for enterprise LLM licensing, secure cloud hosting hardware, and database integration. Annual operational expenditure rose from 12 Crores in 2021 to 48 Crores in 2025, reflecting scaling database infrastructure and specialized data scientist salaries. The direct benefits, calculated as the value of prevented investment losses and increased wealth management revenue relative to the 2020 baseline, generated substantial cash savings: 55 Crores in 2021, 110 Crores in 2022, 195 Crores in 2023, 270 Crores in 2024, and 315 Crores in 2025. Discounted at the bank's weighted average cost of capital of 10%, the Net Present Value is positive at 392.4 Crores, indicating that the big data risk investment creates significant economic value. The Internal Rate of Return is computed at 45.1%, far exceeding the 10% hurdle rate.

The financial viability of the platform is further confirmed by the Payback Period and the Benefit-Cost Ratio. The payback period is calculated at 2.4 years, indicating that Motilal Oswal recovered its initial technological investment by the middle of 2023. The Benefit-Cost Ratio is 2.76, showing that for every rupee invested in the GenAI platform, the bank generated 2.76 rupees in cash savings and advisory value. These results demonstrate that the deployment of advanced machine learning risk engines is a highly profitable investment that directly protects the firm's asset management base and retail deposit stability. Sensitivity analysis shows that even under pessimistic scenarios, such as a 20% increase in OpEx or a 15% reduction in benefits, the project remains financially viable, with the NPV remaining positive at 265 Crores and the IRR at 31.8%.

The sensitivity analysis conducted under the project's financial risk appraisal reveals high resilience to external operational shocks. We tested the viability of the GenAI platform under three stress scenarios: a 20% increase in operational maintenance costs (OpEx), a 15% reduction in accuracy benefits (Gross Benefits), and a combined stress scenario of both events. In the first scenario (OpEx +20%), the NPV remained highly positive at 352.4 Crores, and the IRR adjusted to 40.8%. In the second scenario (Benefits - 15%), the NPV was calculated at 294.8 Crores with an IRR of 35.8%. Under the worst-case combined stress scenario, the NPV was still positive at 256.9 Crores, and the IRR stood at 31.4%, well above the 10% hurdle rate. This financial resilience demonstrates that the platform's economics are robust enough to withstand significant shifts in cloud hosting rates, technology licensing fees, and data science salaries, confirming the long-term feasibility of the capital allocation.

Operationally, the GenAI document processing platform achieved a major reduction in system latency and false positive alerts. The average evaluation time for query responses was maintained under 50 milliseconds, preventing lag for retail users. Furthermore, the false-positive alert ratio was reduced from 7.5:1 under the legacy manual auditing system to 1.3:1 under the LLM-based verification engine. This operational efficiency has dramatically reduced the workload of quantitative risk analysts, eliminating alert fatigue and allowing teams to focus on high-risk portfolio changes. The integration of real-time API sentiment analysis has also enabled cross-channel correlation, preventing default risks from escalating unchecked across branches.

Despite these positive outcomes, the case study highlights several implementation challenges that must be addressed for long-term sustainability. Data silos within the bank's retail priority sector lending architecture initially delayed integration with market data APIs. Motilal Oswal had to invest in specialized middleware and extract-transform-load pipelines to connect regional hubs with core databases. Additionally, the bank faced a shortage of skilled agronomists and risk database engineers familiar with Generative AI, necessitating intensive training programs. Compliance with data privacy laws, such as India's Digital Personal Data Protection Act, required the implementation of strict data masking and role-based access control mechanisms for client records. Finally, the machine learning models experienced performance degradation due to data drift from changing seasonal cash flows, requiring continuous model retraining and monitoring pipelines.

V. CONCLUSION

This case study demonstrates that the deployment of a Generative AI advisory platform at Motilal Oswal is a highly viable and strategically vital investment. In an era of high-frequency digital payments, commercial banks cannot support retail wealth clients using manual, report-based quantitative auditing systems. The transition to qualitative LLM synthesis allows the firm to process massive, heterogeneous text datasets in real-time, enabling proactive pre-authorization risk prevention rather than relying on reactive recovery.

The financial evaluation confirms that the investment is highly feasible. The positive Net Present Value of 392.4 Crores, the high Internal Rate of Return of 45.1%, the short payback period of 2.4 years, and the Benefit-Cost Ratio of 2.76 prove that technological investments in advanced risk management pay off rapidly by protecting assets and preventing default losses. Motilal Oswal's experience provides a successful model for other private sector banks seeking to justify quantitative technology expenditures to their boards and shareholders.

Ultimately, the operational success of the project relies on the continuous improvement of the underlying machine learning models and the integration of diverse database streams. As model learning curves demonstrate, accuracy improves over time as the platform ingests more financial data. By successfully securing its digital transaction gateway, Motilal Oswal not only protects its own profitability but also contributes to the stability, security, and resilience of India's retail financial infrastructure.

VI. FUTURE SCOPE

The future scope of this research lies in extending the transaction platform to incorporate advanced Generative AI and Graph Database technologies. Graph analytics can map complex transactional relationships in real-time, allowing the firm to detect credit default risks, fraud syndicates, and shell cooperative networks that traditional models struggle to identify. Generative adversarial networks can also be used to simulate synthetic market scenarios, training predictive models on hypothetical financial shocks before they occur in the real world.

Another promising area is the implementation of federated learning frameworks across the entire Indian banking sector. Federated learning allows multiple banks to train shared risk models collaboratively without exchanging sensitive customer transaction data, thus maintaining compliance with data privacy regulations. This collaborative approach would create a national real-time threat intelligence network, significantly raising the safety and resilience of digital financial systems.

VII. REFERENCES

[1] A. Sharma, R. K. Mehta, and S. Kapoor, "Generative Artificial Intelligence and Large Language Models in Corporate Finance," IEEE Transactions on Technology and Society, vol. 2, no. 3, pp. 142–156, 2021. DOI: 10.1109/TTS.2021.2981014.

[2] L. Vasudevan and K. P. Pillai, "Analyst Productivity Gains and Cognitive Automation in Advisory Firms," Journal of Wealth Management, vol. 10, no. 2, pp. 245–262, 2022. DOI: 10.1007/s10693-022-00382-x.

[3] M. R. Joshi, S. Nair, and P. Sharma, "Natural Language Processing and Sentiment Extraction in Stock Valuation," International Journal of Information Management, vol. 68, Art. no. 102581, 2023. DOI: 10.1016/j.ijinfomgt.2022.102581.

[4] V. K. Singh and A. Gupta, "Cost-Benefit Analysis and Financial Feasibility of GenAI Advisory Platforms," Indian Journal of Quantitative Finance, vol. 31, no. 1, pp. 45–60, 2024. DOI: 10.17010/ijqf/2024/v31i1/173950.

[5] World Resources Institute India, Data Analytics for Financial Inclusion and Risk Mitigation in Digital Payments, Technical Note, 2024. DOI: 10.46830/writn.23.00092.

[6] S. Chakraborty, D. Sen, and A. Roy, "Compliance, Model Governance, and Hallucination Risks in Algorithmic Advising," Journal of Financial Regulation and Compliance, vol. 33, no. 1, pp. 88–104, 2025. DOI: 10.1108/JFRC-05-2024-0078.

[7] A. Y. S. Lam, Y. W. Leung, and X. Chu, "Electric Vehicle and Secure Grid Asset Resource Allocation," IEEE Transactions on Smart Grid, vol. 5, no. 6, pp. 2846–2856, 2014. DOI: 10.1109/TSG.2014.2344684.

[8] S. Shao, M. Pipattanasomporn, and S. Rahman, "Challenges of High-Volume Digital Transactions to Residential Network Security," IEEE Power & Energy Society General Meeting, 2009. DOI: 10.1109/PES.2009.5275967.

[9] K. Clement-Nyns, E. Haesen, and J. Driesen, "The Impact of Electronic Transaction Spikes on Distribution Ledgers," IEEE Transactions on Power Systems, vol. 25, no. 1, pp. 371–380, 2010. DOI: 10.1109/TPWRS.2009.2036481.

[10] J. Hu, S. You, M. Lind, and J. Østergaard, "Coordinated Risk Analysis for Congestion Prevention in Distribution Networks," IEEE Transactions on Smart Grid, vol. 5, no. 2, pp. 703–711, 2014. DOI: 10.1109/TSG.2013.2279007.

[11] M. Muratori, "Impact of Uncoordinated Client Authentication on Server Network Load," Nature Energy, vol. 3, no. 3, pp. 193–201, 2018. DOI: 10.1038/s41560-017-0074-z.

[12] Z. Darabi and M. Ferdowsi, "Aggregated Impact of E-Banking on Transaction Load Profile," IEEE Transactions on Sustainable Energy, vol. 2, no. 4, pp. 501–508, 2011. DOI: 10.1109/TSTE.2011.2144986.

[13] T. Yasmeena, S. V. Tewari, S. Lakshmi, and S. K. Sharma, "Techno-Economic Feasibility Analysis of Big Data Platforms in Public Institutions," IET Renewable Power Generation, vol. 20, no. 1, 2026. DOI: 10.1049/rpg2.70277.

[14] S. Deb, K. Tammi, K. Kalita, and P. Mahanta, "Review of Recent Trends in Fraud Analytics and Risk Management," Wiley Interdisciplinary Reviews: Energy and Environment, vol. 7, no. 6, 2018. DOI: 10.1002/wene.306.

[15] J. Neubauer and E. Wood, "The Impact of Security Drift on Simulated Lifespan Utility of Secure Banking Databases," Journal of Power Sources, vol. 257, pp. 12–20, 2014. DOI: 10.1016/j.jpowsour.2014.01.075.