COLOMBO SCIENTIFIC PUBLISHING

INTERNATIONAL JOURNAL OF COMPUTER SCIENCE & INFORMATION SYSTEM (IJCSIS)

E-ISSN: 2536-7919
P-ISSN: 2536-7900

PAGE NO: 29-34

Artificial Intelligence, Corporate Finance, and Regulatory Compliance: Integrative Frameworks for Fraud Risk Management, Governance, and Ethical Automation

Dr. Elena Marquez
Global Institute for Financial Systems, Universidad Internacional

ARTICLE INFO

Article history:
Submission: August 18 2025
Accepted: August 24, 2025
Published: August 30, 2025

VOLUME: Vol.10 Issue 08 2025

Keywords:
Artificial intelligence; corporate finance; regulatory compliance; fraud risk management; governance; automation; interpretability

ABSTRACT

This article synthesizes contemporary scholarship on the application of artificial intelligence (AI) within corporate finance, regulatory compliance, and fraud risk management to propose an integrative theoretical and practical framework. Drawing on recent empirical and conceptual studies that examine AI-enabled decision-support systems, natural language processing, machine learning pipelines, robotic process automation, and governance-oriented automation, the paper foregrounds how these technologies reconfigure the detection, prevention, and oversight functions that underpin corporate financial integrity. The abstracted contributions are threefold. First, the article develops a layered taxonomy linking AI capabilities (predictive modeling, anomaly detection, transaction monitoring, text analytics) to specific corporate finance functions (reporting quality, treasury operations, audit trails, regulatory reporting), highlighting the pathways through which AI can enhance efficiency and decision quality while introducing new operational and ethical risks (Rane, 2024; Hassan et al., 2023). Second, it elaborates design principles for ethically scalable automation and governance architectures that reconcile performance with regulatory transparency and accountability (Lin, 2024; Ajmal et al., 2025; Adeyelu et al., 2024). Third, the paper advances concrete approaches for AI-driven fraud risk management that combine model robustness, human-in-the-loop processes, interpretability, and regulatory oversight practices for emerging markets with constrained institutional capacity (Asad, 2025; Aziza et al., 2023). Throughout, the analysis critically examines trade-offs—between automation and human judgment, predictive power and fairness, throughput and auditability—offering prescriptive recommendations for practitioners, policymakers, and researchers. The article concludes with a research agenda identifying pressing empirical tests, methodological improvements, and policy reforms needed to realize AI's promise in corporate finance without compromising governance, financial stability, or equitable outcomes.

INTRODUCTION

The acceleration of artificial intelligence (AI) adoption across corporate functions has been particularly pronounced in the financial domain, where algorithms increasingly inform forecasting, reporting, credit decisions, and control activities (Rane, 2024; Hassan et al., 2023). Organizations are deploying machine learning models to automate routine processes, apply predictive analytics to financial time series, and use natural language processing (NLP) to parse regulatory text and communications (Rane, 2024; Lin, 2024). Concurrently, regulators and compliance officers face the dual challenge of leveraging AI to improve oversight while ensuring that automated systems do not undermine fairness, transparency, or accountability (Ajmal et al., 2025; Adeyelu et al., 2024).

This paper situates itself at the intersection of corporate finance, fraud risk management, and regulatory compliance. The impetus for this synthesis arises from three converging trends. First, firms are under pressure to increase operational efficiency and reduce manual processing costs, creating incentives to adopt AI-driven automation in financial reporting and control functions (Rane, 2024; Singh, 2024). Second, the complexity and velocity of financial transactions have made traditional detection approaches less effective, elevating the need for advanced analytics capable of identifying subtle, adaptive fraud patterns (Hassan et al., 2023; Asad, 2025). Third, regulatory environments are becoming more dynamic and data-intensive, necessitating tools that can support compliance at scale while enabling auditability and interpretability (Ajmal et al., 2025; Adeyelu et al., 2024).

Despite the promise, the literature identifies critical gaps. Empirical work remains fragmented: studies often focus narrowly on single technologies or domains (e.g., NLP for regulatory text), leaving a need for integrative frameworks that map capabilities to governance outcomes (Challoumis, 2024; Aziza et al., 2023). Moreover, ethical and operational risks—model bias, opaque decision logic, adversarial manipulation, and automation-induced errors—are insufficiently addressed by existing corporate governance mechanisms (Agu et al., 2024; Omoteso & Mobolaji, 2020). Emerging markets, with particular institutional constraints and regulatory capacity limitations, require tailored approaches that balance innovation with safeguards (Asad, 2025; IFC, 2020).

The primary objective of this article is to generate a comprehensive, publication-ready synthesis and theory-driven framework that: (1) articulates the ways AI augments corporate finance and compliance processes; (2) defines governance and technical design principles for ethical, accountable automation; and (3) prescribes pragmatic strategies for AI-enabled fraud risk management, particularly in contexts with variable regulatory capacity. By integrating the conceptual and empirical insights from the provided references, the paper offers a roadmap for practitioners and regulators to adopt AI responsibly in financial operations and for researchers to fill the evident empirical and methodological gaps.

METHODOLOGY

This paper adopts a rigorous integrative review methodology designed to synthesize heterogeneous literature into a cohesive theoretical framework and set of actionable recommendations. Integrative reviews depart from narrow systematic reviews by accommodating empirical studies, theoretical contributions, policy reports, and practitioner analyses in order to construct broader conceptualizations and research agendas (Challoumis, 2024; Lin, 2024).

The methodological approach unfolds in three analytic stages. First, thematic mapping identifies recurring constructs across the reference corpus—AI technologies, corporate finance functions, compliance tasks, governance mechanisms, and ethical risks. Each reference was coded for which constructs it addressed (e.g., Rane, 2024 coded for AI in corporate finance and NLP; Hassan et al., 2023 for fraud prevention and compliance). Cross-referencing yielded clusters that form the backbone of the framework (Ajmal et al., 2025; Adeyelu et al., 2024).

Second, capability-to-function alignment establishes how specific AI capabilities (supervised learning for anomaly detection, unsupervised clustering for pattern discovery, NLP for documentation analysis, robotic process automation for transaction handling) map to discrete corporate finance tasks (financial reporting, internal control, treasury operations, external disclosures). This mapping is based on the functional descriptions and case scenarios discussed in empirical and conceptual works (Rane, 2024; Hassan et al., 2023; Agarwal & Kumar, 2017).

Third, a normative design synthesis combines technical considerations (model robustness, interpretability, data governance) with governance principles (transparency, accountability, human oversight) to propose architectures and procedural protocols for ethical automation (Lin, 2024; Ajmal et al., 2025). The synthesis leverages regulatory-focused literature examining AI compliance use-cases (Adeyelu et al., 2024; Aziza et al., 2023), and market-specific analyses addressing emerging market constraints (Asad, 2025; IFC, 2020).

Throughout, the article emphasizes descriptive rather than quantitative meta-analytic claims: given the heterogeneity of methods and contexts in the references, the goal is conceptual integration, theoretical elaboration, and normative guidance rather than pooled effect-size estimation. Every major claim draws explicitly on one or more provided sources, using (Author, Year) citations to maintain traceability and to ground assertions in the supplied corpus (Rane, 2024; Hassan et al., 2023; Lin, 2024).

Results

The integrative analysis yields four primary results: (1) a layered taxonomy linking AI capabilities to corporate finance and compliance functions; (2) a governance-technology architecture for ethically scalable automation; (3) an operational model for AI-driven fraud risk management tailored to emerging markets; and (4) an identification of persistent empirical and methodological gaps requiring research attention.

1. Layered Taxonomy of AI Capabilities and Financial Functions

The taxonomy organizes AI capabilities into three interrelated layers—Observation, Inference, and Action—and aligns each with corporate finance and compliance functions.

Observation: This layer comprises data acquisition, feature engineering, and NLP-driven document parsing. NLP enables automated extraction of contractual terms, regulatory clauses, and narrative disclosures, thereby supporting continuous compliance monitoring (Rane, 2024; Lin, 2024). Unsupervised feature extraction assists with high-dimensional financial records (Agarwal & Kumar, 2017).

Inference: The inference layer includes predictive models, anomaly detection algorithms, clustering, and causal inference techniques. Supervised models trained on labeled loss events can estimate the probability of fraud or reporting irregularities, while unsupervised methods detect emergent patterns that escape rule-based systems (Hassan et al., 2023; Adeyelu et al., 2024).

Action: The action layer operationalizes model outputs via robotic process automation (RPA), transaction filters, alerting systems, and decision-support dashboards. RPA can execute standardized remediation steps (e.g., transaction holds), but must be coupled with human oversight to manage exceptions and ambiguous cases (Rane, 2024; Ajmal et al., 2025).

This layered mapping clarifies how end-to-end AI pipelines function within finance organizations and highlights where governance interventions should be inserted—particularly at the interfaces between inference outputs and automated actions to preserve accountability (Lin, 2024; Ajmal et al., 2025).

2. Governance-Technology Architecture for Ethical Automation

From the synthesis emerges a governance-technology architecture with four foundational components: data governance and provenance, model lifecycle management, interpretability and explainability, and human-in-the-loop enforcement mechanisms.

Data Governance and Provenance: Robust input data controls are critical for preventing downstream biases and misrepresentations. Provenance metadata, lineage tracking, and access controls are necessary to ensure auditability and regulatory reporting fidelity (Adeyelu et al., 2024; Omoteso & Mobolaji, 2020).

Model Lifecycle Management: Versioning, monitoring, and retraining protocols must be formalized. Model risk should be incorporated into corporate risk registers, with regular stress-testing and scenario analyses to surface vulnerabilities (Rane, 2024; Singh, 2024).

Interpretability and Explainability: For regulatory compliance and stakeholder accountability, models must provide intelligible rationales for decisions, especially in high-stakes contexts like fraud detection or financial reporting adjustments (Lin, 2024; Agu et al., 2024).

Human-in-the-Loop Enforcement: Automation must not obviate human responsibility. Human oversight, escalation procedures, and exception-review workflows are central to ensuring ethical outcomes and regulatory compliance (Ajmal et al., 2025; Adeyelu et al., 2024).

The architecture emphasizes that organizational governance must co-evolve with technical deployments to mitigate risks such as model drift, adversarial exploitation, and unintended discriminatory impacts (Agu et al., 2024; Omoteso & Mobolaji, 2020).

3.Operational Model for AI-Driven Fraud Risk Management in Emerging Markets

Emerging markets present distinctive regulatory and infrastructural constraints—less consistent data availability, variable enforcement capacity, and constrained technological infrastructure (Asad, 2025; IFC, 2020). The analysis suggests an operational model tailored to these realities:

Data-light Detection: Employ algorithms that require limited labeled data, such as semi-supervised or anomaly-detection approaches, to compensate for sparse fraud labels (Hassan et al., 2023; Agarwal & Kumar, 2017).

Regulatory Collaboration Networks: Create data-sharing consortia and anonymized information exchanges across financial institutions to improve signal detection, subject to privacy and confidentiality safeguards (Asad, 2025).

Capacity-building Protocols: Augment AI deployments with regulatory training programs and prescriptive compliance playbooks that strengthen oversight capabilities without requiring sophisticated in-house ML expertise (Ajmal et al., 2025; IFC, 2020).

Transparency-by-Design: Incorporate clear documentation and model cards that can be reviewed by auditors and regulators, reducing asymmetries in technical understanding (Lin, 2024; Adeyelu et al., 2024).

This operational model balances the need for effective fraud detection with institutional realities, reinforcing the premise that technological sophistication must be accompanied by governance innovation (Aziza et al., 2023; Asad, 2025).

4.Gaps and Limitations Identified in the Literature

While the literature provides numerous technical and conceptual contributions, the integrative review reveals persistent gaps: limited longitudinal studies measuring AI's impact on reporting quality and fraud incidence (Zhou et al., 2022; Rane, 2024); inadequate frameworks for cross-jurisdictional regulatory cooperation in AI oversight (Ajmal et al., 2025); and an underdeveloped body of work addressing adversarial threats to financial AI systems (Agu et al., 2024). Addressing these gaps is essential for translating promising pilots into scalable, trustworthy systems.

DISCUSSION

The results underscore AI's transformative potential in corporate finance and regulation, while simultaneously illuminating complex governance challenges that require multidisciplinary solutions. This discussion elaborates theoretical implications, counters potential objections, and outlines a forward-looking agenda.

Theoretical Implications: Toward a Socio-Technical Theory of Financial Automation

The findings support a socio-technical framing in which AI systems are not mere tools but integral components of organizational systems that reshape decision authority, informational flows, and accountability structures (Omoteso & Mobolaji, 2020; Lin, 2024). The layered taxonomy points to the need for theories that connect technological affordances to institutional arrangements: models that predict how automation alters incentive structures, audit practices, and disclosure behaviors. For example, if RPA reduces transaction processing times significantly, internal control checkpoints may need redesign to preserve checks-and-balances—an adjustment that is both technical and organizational (Rane, 2024; Singh, 2024).

Trade-offs and Counter-Arguments: Accuracy Versus Accountability

High predictive accuracy often correlates with increased model complexity and reduced interpretability. Some practitioners might prioritize performance metrics and cost-savings (Hassan et al., 2023), but the sovereignty of accountability in finance necessitates interpretability and auditability (Lin, 2024). The recommended governance architecture responds by prescribing tiered model usage: highly automated, less interpretable models may be acceptable in low-impact scenarios (e.g., internal triage), while high-stakes decisions (e.g., reporting adjustments, regulatory filings) should rely on interpretable or human-augmented models. This stratified approach respects both technological advantages and governance imperatives.

Equity, Bias, and Fairness Concerns

AI models trained on historical financial data may perpetuate biases embedded within prior decisions or socioeconomic disparities, contributing to unfair treatment in credit, employment-linked finance, or supplier payments (Agu et al., 2024). Ethical automation requires active bias identification, fairness-aware training, and governance mechanisms that monitor disparate impacts. Such measures must be routine parts of compliance processes rather than afterthoughts (Adeyelu et al., 2024; Omoteso & Mobolaji, 2020).

Operational Risks: Adversarial Manipulation and Model Robustness

Adversaries, including sophisticated fraud rings, may attempt to exploit model vulnerabilities through data poisoning or evasion strategies. The literature on adversarial robustness emphasizes proactive defenses—data validation, anomaly monitoring, and adversarial testing—but financial institutions have been slow to integrate adversarial threat models into their ML lifecycle management (Agu et al., 2024). Embedding adversarial scenario planning in model governance is necessary to maintain the reliability of detection systems.

Regulatory and Policy Implications

Regulators face the paradox of needing technical sophistication to oversee AI systems while also ensuring that compliance requirements remain tractable for regulated firms. Policy instruments can facilitate responsible adoption: standardized reporting templates for AI use in finance, mandatory documentation (model cards), and supervisory stress-testing of critical ML systems (Ajmal et al., 2025; Lin, 2024). For emerging markets, technical assistance and collaborative regulatory sandboxes can lower barriers to safe experimentation (Asad, 2025; IFC, 2020).

Limitations of the Synthesis

This integrative review relies exclusively on the provided references, which vary in methodological rigor and contextual specificity. While these sources offer valuable insights, the synthesis is limited by their heterogeneity and the uneven empirical coverage—particularly the scarcity of longitudinal, multi-jurisdictional studies that could empirically validate long-term impacts (Zhou et al., 2022; Rane, 2024). Future empirical work should prioritize standardized metrics and multi-site studies to refine causal inferences about AI's effects on governance and fraud incidence.

Future Research Directions

To operationalize the framework and address outstanding uncertainties, the following research agenda is proposed:

1.Longitudinal Impact Studies: Track firms that adopt AI-enabled compliance solutions over multiple years to measure effects on reporting quality, fraud rates, and compliance costs (Zhou et al., 2022).

2.Comparative Case Studies: Analyze differences across jurisdictions, firm sizes, and sectors to identify contextual moderators of AI effectiveness (Aziza et al., 2023; IFC, 2020).

3.Adversarial Robustness in Finance: Develop domain-specific adversarial threat models and defense mechanisms tailored to transactional and reporting data (Agu et al., 2024).

4.Human-AI Interaction Experiments: Empirically test different human-in-the-loop configurations to determine optimal mixes of automation and human judgment for various finance tasks (Lin, 2024).

5.Policy Evaluation Studies: Assess the efficacy of regulatory instruments (model documentation requirements, sandboxing, data-sharing consortia) through pilot implementations and controlled evaluations (Ajmal et al., 2025; Asad, 2025).

CONCLUSION

AI technologies offer substantial opportunities to enhance corporate finance operations, strengthen fraud detection, and scale compliance activities. However, realizing this potential requires moving beyond ad hoc deployment toward integrated socio-technical systems that couple robust technical design with organizational governance and regulatory oversight. The layered taxonomy and governance architecture proposed in this paper provide a blueprint for aligning AI capabilities with finance functions in ways that prioritize accountability, interpretability, and fairness. For emerging markets, tailored operational models that emphasize data-light methods, regulatory collaboration, and capacity-building are essential. Addressing the identified empirical and methodological gaps will require concerted efforts from scholars, practitioners, and policymakers, but the prize—more efficient, transparent, and resilient financial systems—is worth the endeavor.

REFERENCES

1. Rane, N. L., Choudhary, S. P., & Rane, J. (2024). Artificial Intelligence-driven corporate finance: enhancing efficiency and decision-making through machine learning, natural language processing, and robotic process automation in corporate governance and sustainability. Studies in Economics and Business Relations, 5(2), 1-22.
2. Asad, F. (2025). AI-Driven Strategies for Fraud Risk Management in Emerging Markets: Enhancing Regulatory Oversight and Digital Transparency.
3. Hassan, M., Aziz, L. A. R., & Andriansyah, Y. (2023). The role artificial intelligence in modern banking: an exploration of AI-driven approaches for enhanced fraud prevention, risk management, and regulatory compliance. Reviews of Contemporary Business Analytics, 6(1), 110-132.
4. Challoumis, C. (2024, November). THE LANDSCAPE OF AI IN FINANCE. In XVII

International Scientific Conference (pp. 109-144).

5. Ajmal, C. S., Yerram, S., Abishek, V., Nizam, V. M., Aglave, G., Patnam, J. D., ... & Srivastava, S. (2025). Innovative Approaches in Regulatory Affairs: Leveraging Artificial Intelligence and Machine Learning for Efficient Compliance and Decision-Making. The AAPS Journal, 27(1), 22.
6. Lin, H. (2024). Ethical and Scalable Automation: A Governance and Compliance Framework for Business Applications. arXiv preprint arXiv:2409.16872.
7. Adeyelu, O. O., Ugochukwu, C. E., & Shonibare, M. A. (2024). Automating Financial Regulatory Compliance with AI: A Review and Application Scenarios. Finance & Accounting Research Journal, 6(4), 580-601.
8. Singh, V. (2024). The impact of artificial intelligence on compliance and regulatory reporting. Journal of Electrical Systems, 20, 4322-4328.
9. Shrivastava, P., Mathew, E. B., Yadav, A., Bezbaruah, P. P., & Borah, M. D. (2014). Smoke Alarm-Analyzer and Site Evacuation System.
10. Agarwal, A. V., & Kumar, S. (2017, November). Unsupervised data responsive based monitoring of fields. In 2017 International Conference on Inventive Computing and Informatics (ICICI) (pp. 184-188). IEEE.
11. Aziza, O. R., Uzougbo, N. S., & Ugwu, M. C. (2023). The impact of artificial intelligence on regulatory compliance in the oil and gas industry. World Journal of Advanced Research and Reviews, 19(3), 1559-1570.
12. Unobe, E. C. (2022). Justice mirage? Sierra Leone's truth and reconciliation commission and local women's experiences. Peace and Conflict: Journal of Peace Psychology, 28(4), 429.
13. Agarwal, A. V., Verma, N., Saha, S., & Kumar, S. (2018). Dynamic Detection and Prevention of Denial of Service and Peer Attacks with IP Address Processing. Recent Findings in Intelligent Computing Techniques: Proceedings of the 5th ICACNI 2017, Volume 1, 707, 139.
14. Al-Rahahleh, A. Corporate Governance Practices and Financial Performance: Evidence from Jordan. International Journal of Business Management, 2017, 12, 123–134.
15. International Finance Corporation. Corporate Governance in MENA: Challenges and Recommendations. International Finance Corporation, Washington, DC, USA, 2020.
16. Kayed, R., & Hassan, M.K. Corporate Governance and Financial Performance in Jordanian Firms. Journal of Emerging Market Finance, 2019, 18, 299–321.
17. Hazaimeh, A., Altarawneh, M., & Al-Hadidi, A. Challenges of Corporate Governance in Emerging Markets: The Case of Jordan. Arab Journal of Governance Studies, 2021, 4, 67–85.
18. Zhou, Y., Zhang, X., & Li, M. The Impact of AI on Financial Reporting Quality: Evidence from Emerging Markets. Accounting AI Journal, 2022, 10, 44–61.
19. Agu, E. E., Abhulimen, A. O., Obiki-Osafiele, A. N., Osundare, O. S., Adeniran, I. A., & Efunniyi, C. P. (2024). Discussing ethical considerations and solutions for ensuring fairness in AI-driven financial services. Engineering Science and Technology Journal, 5, 1–9.
20. Omoteso, K., & Mobolaji, H. AI and Corporate Governance: Enhancing Transparency in Financial Reporting. Journal of Business Ethics, 2020, 165, 789–805.