

Artificial Intelligence in Financial Analytics: An Integrative Review of Financial Modeling, Forecasting, and Financial Controls

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Abstract

Artificial intelligence (AI) is increasingly applied across finance, including fraud detection, risk assessment, and forecasting, yet forecasting and internal controls are often governed in separate initiatives. This paper examines two pillars of AI use in finance: AI-driven financial modeling and forecasting, and AI-driven reconciliation within internal control over financial reporting (ICFR). The paper is based on a literature review of 23 academic, regulatory, and standards sources, including materials from the SEC, PCAOB, and COSO. The review indicates that the two pillars are interdependent: reconciled, well-governed data underpins reliable forecasting, and continuous reconciliation combined with predictive modeling can support pre-filing risk detection in SEC reporting. Model risk management, explainability, and human sign-off emerge as governance requirements common to both pillars. Building on these insights, the paper proposes a five-stage maturity framework that sequences AI-driven reconciliation ahead of predictive forecasting, together with shared governance practices. The findings suggest that managing forecasting and controls under a unified governance approach offers a coherent pathway for AI adoption in finance.

JEL classification numbers: C53, G17, G32, M41, M42.

Keywords: Artificial Intelligence in Finance, Financial Analytics, Automated Reconciliation, Internal Controls, AI-Driven Finance.

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1. Introduction

AI in finance broadly refers to the application of AI techniques, from machine learning to deep learning and generative AI, across financial businesses, a research area that has attracted industry attention for a long time and continues to expand into new domains of finance, economics, and society (Cao, 2022). AI has been applied in the financial industry to areas such as fraud detection, risk assessment, and personalized financial advice (Harvey Weinstein et al., 2026).

This paper mainly highlights two areas of AI usage in finance and controls functions:

1. Financial modeling and prediction: using AI to forecast financial outcomes (revenue, cash flow, risk, demand) with greater speed and accuracy than traditional statistical or spreadsheet-based methods.
2. Data reconciliation and financial controls: using AI to match, validate, and reconcile financial data across the many systems an organization operates (ERP systems (Enterprise Resource Planning), banking platforms, sub-ledgers), thereby strengthening the internal controls that protect the integrity of financial reporting.

The paper also examines the interdependency of these two pillars. The reconciled, well-governed data is the foundation on which trustworthy predictive models are built, and both pillars share a common set of risk-management and governance challenges that the organizations should address jointly rather than in separate initiatives.

2. Methodology

This paper is based on a literature review conducted across academic and institutional databases, including IEEE Xplore, Google Scholar, arXiv, preprints, and journal publishers. The search strategy focused mostly on AI in financial environment, AI in auditing and robotic process automation as well as usage in internal controls and compliance frameworks. Regulatory and standards sources (SEC, PCAOB, COSO) were also obtained from issuing bodies. The final reference list comprises exactly 23 sources. Results from the research were screened for relevance, prioritizing peer-reviewed journal articles as well as preprints of academic reports.

3. Pillar 1: AI-Driven Financial Modeling and Forecasting

3.1 Transition from Traditional Analytics to Modern AI

Financial forecasting has historically relied on statistical methods like regression, time-series models, and spreadsheets. Traditional methods struggle with large, heterogeneous datasets and are slow to update. A broad ecosystem of AI and data-science techniques can be applied to resolve these issues, such as market trend forecasting, stock price prediction, credit scoring, and portfolio risk estimation, spanning classical machine learning, evolutionary computing, and, increasingly, deep learning (Cao, 2022).

Machine learning models are replacing traditional spreadsheet-based forecasting approaches with dynamic forecasts by incorporating historical and other relevant financial information (Cao, 2022).

3.2 Techniques and Applications

1. Supervised machine learning: Models such as gradient-boosted trees and neural networks trained on historical, labeled data to predict outcomes like default probability, transaction fraud likelihood, or customer churn (Cao, 2022).
2. Natural language processing (NLP): Extraction of signals from unstructured sources like analyst reports, news, earnings calls, and sentiment data to facilitate quantitative forecasts (Cao, 2022).
3. Generative AI: Emerging use of large language models for data augmentation, feature extraction, and improving the interpretability of financial risk forecasts (Yao et al., 2025).
4. Rolling and scenario-based forecasting: Utilizing machine learning models to continuously update projections and scenario analysis by incorporating changing financial and operational information into predictive models (Cao, 2022).
5. Explainable AI (XAI): Techniques such as SHAP and LIME that make model outputs interpretable, addressing the "black box" problem that has historically made finance leaders hesitant to trust automated forecasts, and which is increasingly expected by regulators (Arsenault et al., 2024; Bowden et al., 2024).

3.3 Benefits of AI-Based Models

Modern financial planning environments can integrate predictive models into forecasting workflows, bridging the long-standing gap between analytical modeling and financial strategy (Cao, 2022).

Generative approaches have been reported to improve both the accuracy and interpretability of financial risk prediction (Yao et al., 2025).

3.4 Challenges

A study shows that while AI improves forecasting accuracy in predictive modeling and reduces false positives for tasks like fraud detection, companies must exercise caution, as these gains must be weighed against new risks emerging from the utilization of these AI techniques (Joshi, 2025).

1. Model opacity: Complex models (particularly deep learning and generative approaches) can outperform simpler methods while being harder to explain to auditors, regulators, or business stakeholders (Arsenault et al., 2024; Bowden et al., 2024).
2. Regulatory and governance uncertainty: As AI-generated forecasts inform real financial and strategic decisions, questions about model validation, version control, and monitoring become genuine compliance concerns rather than purely technical ones (Joshi, 2025).

3. Generative-AI-specific risks: Emerging threats like compromised data provenance and adversarial AI vulnerabilities fall outside the scope of legacy model risk management (MRM) frameworks. This requires the organization to update the risk and governance models (Yao et al., 2025).

4. Pillar 2: Automating Reconciliation and Internal Controls

Financial reconciliation is the process of comparing independent sets of records and identifying discrepancies between them. Because reconciliation involves repetitive and manual activities, it represents a potential area for process automation (Moffitt et al., 2018). Robotic process automation (RPA) addresses rule-based repetition, whereas AI-based methods extend automation to cases involving variance and judgment (Christophides et al., 2020; Moffitt et al., 2018).

4.1 Introduction to Reconciliation

Reconciliation is not merely an operational task. It is frequently a key control relied upon to detect or prevent material misstatement in financial statements, placing it within the scope of internal control over financial reporting (ICFR) under Section 404 of the Sarbanes-Oxley (SOX) Act and Item 308 of Regulation S-K (Sarbanes-Oxley Act, 2002; SEC, 2003), which is typically performed using the COSO Internal Control Integrated Framework (COSO, 2013). Management also evaluates disclosure controls and procedures under Item 307 of Regulation S-K and Exchange Act Rule 13a-15 (SEC, 2003).

Because reconciliation sits at this intersection of efficiency and control, automating it has direct implications for control design, evidence retention, and audit readiness, and it is not limited to processing speed.

4.2 AI in Reconciliation and Control Automation

1. Entity resolution and probabilistic matching: Unlike traditional rules-based systems, these models can successfully handle one-to-many and many-to-many reconciliations by accommodating minor variances in amounts, dates, and descriptions (Christophides et al., 2020). Probabilistic matching also introduces a distinct control risk; a false positive match can clear a genuine discrepancy. Match confidence thresholds and tolerances should be set according to materiality, validated against historical exceptions, and monitored for precision.
2. Machine learning anomaly detection: Machine learning methods can be applied to financial reporting data to identify patterns associated with potential misstatement and other financial risks, providing a basis for earlier investigation, before they reach final reporting (Zavitsanos et al., 2025).
3. Automated record linkage: By deploying machine learning workflows under a strict governance layer, organizations can continuously match complex transactions and generate probabilistic resolution suggestions rather than executing them unilaterally (Christophides et al., 2020).

4. Continuous reconciliation: AI-enabled matching can support a shift from periodic reconciliation toward more continuously monitored financial data and exceptions.

4.3 Potential Benefits

As companies adopt AI across finance teams, a more continuous reconciliation process can also provide earlier visibility into discrepancies rather than concentrating reconciliation activity at end of period. It also enables employees to free up capacity to focus on higher value analytics driven tasks. While these benefits are plausible, they remain unquantified.

4.4 Risk and Governance Considerations

As AI moves into a role that directly affects the preparation, review, or approval of financial statements, it becomes subject to the applicable control, audit, and governance requirements for control-relevant technology (PCAOB, 2010). Where these workflows include generative components, COSO's 2026 guidance on generative AI also applies (COSO, 2026). The risks below are attributed accordingly to generative models or to non-generative models (probabilistic matching, record linkage, and anomaly detection).

1. Non-reproducibility: Outputs from generative models can vary between runs on identical inputs, complicating the audit trail a control is expected to produce (COSO, 2026). Probabilistic matching and anomaly-detection models present a related but distinct issue: results can change when model versions, match thresholds, or training data change, so each matching outcome should be traceable to the model version and configuration in effect when it was produced.
2. Evidence gaps: Automated matching may not retain the documentation auditors and regulators expect for control testing (PCAOB, 2007), and AI-generated narrative commentary raises the same concern for generative components (COSO, 2026).
3. Model drift: Matching and anomaly-detection models can degrade over time as underlying data patterns shift (for example, counterparties, transaction mix, and description formats change), requiring ongoing monitoring rather than one-time validation (Board of Governors of the Federal Reserve System and Office of the Comptroller of the Currency, 2011; Gama et al., 2014).
4. IT General Control (ITGC) gaps: PCAOB auditing standards require auditors to consider how IT affects financial reporting and to understand relevant manual and automated controls, including IT general controls that are important to the effective operation of automated controls (PCAOB, 2010).

If an AI-enabled reconciliation serves as a key control, failure in its design or operation must be evaluated for severity as a control deficiency (SEC, 2003; COSO, 2013). Management also must be able to support the completeness and accuracy of the AI-generated outputs on which the control relies.

5. Where the Two Pillars Intersect

The relationship between AI-driven prediction and AI-driven reconciliation is not coincidental; they are highly interdependent on each other. Predictive financial models need high-quality, reconciled data as input wherever their targets are measures such as revenue, balances, and cash flow; forecasts driven by operational data, such as demand or pipeline, depend on other data quality controls. In fact, data quality is the prerequisite for building reliable, transparent, and explainable AI systems in regulated domains. This is particularly true in the case of financial data in this digital age, given how heterogeneous, high-velocity, and interdependent financial data sources have become (Saini et al., 2025).

The impact of a lapse in data accuracy, completeness, or timeliness cascades through downstream predictive models. Ultimately, that data degradation can lead to biased forecasts, unstable model behavior, and costly operational errors.

This creates a practical dependency chain relevant to any organization's AI roadmap; we present it as a conceptual proposition rather than an empirically established result (Section 8.1):

1. Reconciliation quality determines data quality, the degree to which records across systems have been matched, validated, and exception resolved. Reconciliation establishes agreement and completeness across systems; it does not by itself establish valuation accuracy.
2. Data quality determines model reliability. If forecasting and prediction models are trained or run on unreconciled, inconsistent data, they will inherit that unreliability, regardless of how sophisticated the modeling technique is.
3. Model reliability determines decision quality; forecasts feed budgeting, resource allocation, and strategic decisions. Hence, any reconciliation failures have an upstream impact that can surface as a strategic misjudgment.

Both pillars speak the exact same governance language. Core concepts like model risk management, explainability (XAI), version control, and continuous monitoring apply almost identically whether the AI is forecasting next quarter's revenue or matching bank transactions to the general ledger. Companies that build separate governance tracks for "AI in FP&A" versus "AI in controls/close" end up duplicating effort. What's worse is that they miss cross-functional risks that only surface when you look at both in conjunction, like a reconciliation-driven data correction that silently invalidates a forecast generated earlier that same day.

6. From Automated Controls to Predictive Modeling

The automated reconciliation and financial forecasting do not just streamline day-to-day operations; they fundamentally change the design and operation of the organization's control activities. When financial data is continuously validated at the source, automated controls do not just act as mere defensive checkpoints, instead it serves as the refined architect for more accurate analytics. By embedding automated controls directly into the financial workflows, organizations will be able to secure data integrity, which is a prerequisite to transition from historical oversight

to reliable and highly assured predictive modeling. It can then be used to share the SEC disclosures on material risks, liquidity and forward-looking guidance. Strengthening internal controls through automation can improve reliability and auditability of the information under public disclosures.

Data quality research indicates that reconciled data is a precondition for reliable forecasting in regulated settings (Saini et al., 2025), although the magnitude of this effect in finance has not, to our knowledge, been quantified (Section 8.1). This section examines the more direct, practical payoff of combining the two pillars: when automated controls and predictive financial modeling operate on the same continuously reconciled data layer, an organization gains the ability to forecast its own future financial reporting, and not be limited to business performance forecasting, with potentially lower risk of error, and ability to catch discrepancies before they reach external filings such as U.S. Securities and Exchange Commission (SEC) reporting.

When transaction-level reconciliation becomes continuous rather than periodic, the exact same matched, validated data is fed into the predictive models. These models can then anticipate how upcoming financial statements will look before the period even ends. Unlike traditional forecasting of operational business that focuses on business outcomes like revenue or cash flow, the prediction target here is the reporting output itself, like projected balances, ratios, and disclosures, which are continuously benchmarked against what automated controls observe in the underlying data.

Machine learning research on financial statement irregularities shows how the underlying mechanics really work: models trained on features like accounts receivable trends, discretionary accruals, and default prediction metrics can flag financial statements at risk of misstatement or fraud. When you build these insights directly into financial reporting and run the models continuously instead of waiting until year-end, the process shifts from post-hoc fraud detection to forward-looking, pre-filing risk scoring (Lokanan & Sharma, 2025; Zavitsanos et al., 2025). The cited studies evaluate models on historical samples; their performance in continuous, pre-filing deployment remains to be demonstrated.

In practice, this creates a feedback loop: automated reconciliation controls clean supply of current data; predictive models use that data to project the financial statements that data will produce; and any divergence between the prediction and the actual closing numbers becomes, itself, an anomaly signal worth investigating before the figures are finalized for reporting.

6.1 How AI Can Help with SEC filing

This approach can give public companies a meaningful advantage during SEC reporting. When the filings are submitted through EDGAR, the system does not just rely on review from the SEC's Division of Corporation Finance; instead, it also goes through automated system-level validation to check syntax, taxonomy compliance, and consistency of calculations against the rigid SEC XBRL filing rules (SEC,

2026). If a filing triggers a system-level validation failure, such as fee data tagging, EDGAR will simply reject or suspend the submission right away, before the filing is accepted (SEC, 2026; SEC, 2021). As early as 2016, the SEC's Division of Economic and Risk Analysis (DERA) described using risk-based data analytics, such as its Corporate Issuer Risk Assessment (CIRA) tool, to identify anomalous patterns in corporate financial reporting that may warrant further inquiry (SEC, 2016). This 2016 account is cited as historical context for analytics-based regulatory review, not as a description of the SEC's current practice.

Automated internal controls that reconcile source data before it is tagged and submitted reduce SEC filing risk in several concrete ways:

1. Pre-filing discrepancy detection: Machine learning-based risk detection can help identify financial-reporting patterns associated with potential misstatement before reporting decisions are finalized (Zavitsanos et al., 2025).
2. XBRL and calculation consistency: Validation tools, whether rules-based or AI-enabled, run tagged data against US GAAP or IFRS taxonomies and prior-period numbers before submission, proactively looking for calculation and taxonomy errors that could otherwise lead to technical rejection or SEC comment letters (SEC, 2026).
3. Consistency across periods and peers: Analytical tools can compare financial information across periods and companies to identify unusual patterns that prompt targeted review before submission, an approach the SEC described as part of its risk-based analytics (SEC, 2016).
4. Anomaly-triggered hold points: Organizations can establish review thresholds that route potentially material discrepancies for human investigation before the filing package is finalized.

6.2 Need for Human Oversight

However, AI does not take away the need for human intervention/accountability. Under SEC regulations, even though software can assist with tag selection and validation, final authentication and sign-off on the electronic filing remain a strict human obligation. Outputs used in disclosure decisions must be legally traceable to a named signatory and the specific source data behind them (SEC, 2020).

This paper recommends that any AI output that triggers a material disclosure carry a human sign-off, validated source data, and the full log of model inputs and its outputs. Such output should be subject to the same evidentiary standard discussed in Section 4 for reconciliation controls generally. Where generative AI is used in a control-relevant or disclosure-related workflow, organizations should additionally apply the governance and verification principles applicable to generative AI (COSO, 2026).

Rather than eliminating human oversight, predictive controls driven by pre-filing checks act as a triage layer. By flagging the figures and disclosures with the highest risk of error, they allow review teams to focus on errors where it is needed the most.

7. A Unified Framework for AI Adoption in Finance

7.1 Controls and Prediction Workflow Roadmap

Since forecasting quality depends heavily on data quality, this framework sequences capabilities by dependency rather than by technology. AI-driven reconciliation and data control capabilities must be prioritized and fully established, meeting a defined readiness level, before ML-based forecasting is introduced and relied upon for decisions or disclosures. Conventional statistical or spreadsheet forecasts may continue in parallel as lower-assurance outputs. Deploying predictive AI models on unreconciled, siloed data across multiple systems risks generating unreliable output. Furthermore, this unreliability can spill over into SEC reporting as well.

7.2 Maturity Stages

This five-stage AI maturity framework is an original conceptual synthesis created for this study. It adapts principles from standard maturity models such as those of Gartner and CMMI, and from research on auditing frameworks, mapping how finance teams can transition from spreadsheet-based reconciliation to real-time AI predictive reporting. The framework has not been empirically validated; the readiness gate criteria are proposals of this paper and not an established standard.

1. Stage 1: Manual and siloed: spreadsheet-based reconciliation and forecasting.
2. Stage 2: Rules-based reconciliation automation: exact-match reconciliation is automated with documented key controls, while forecasting remains conventional (statistical or spreadsheet-based). Manual intervention is still required for judgment steps. No ML-based forecasting models are deployed at this stage.
3. Stage 3: AI-assisted reconciliation and control: Probabilistic matching and anomaly detection are deployed and established across in-scope reconciliations, and all exceptions require mandatory human review. Forecasting remains conventional throughout this stage; no ML-based forecasting model is deployed, in shadow mode or otherwise, until AI-driven reconciliation is fully established. Transition to Stage 4 is gated on meeting data readiness metrics, such as reconciliation coverage, exception aging, and match precision and recall.
4. Stage 4: Continuous and connected: AI agents handle ongoing reconciliation and continuously feed a shared, governed data layer. Only after the Stage 3 readiness gate has been met are predictive forecasting models introduced. They pull directly from the live, reconciled data rather than from stale exports, are first validated in parallel with conventional forecasts, and are relied upon for decisions only once that validation is complete. Agent actions are subject to authorization limits and to segregation of duties.
5. Stage 5: Integrated financial intelligence: At this stage, reconciled, real-time data supplies forecasting, scenario modeling, and filing-ready reporting from a single governed data layer, enabling early risk detection.

Instead of reconciling data at the deadline, organizations rely on predictive models to flag potential pre-filing errors and risks, and AI-generated narrative commentary, subject to human review, supports control reviews and decision-making.

7.3 Shared Governance Practices

1. Standardize model risk management: Practices like version control, drift monitoring, and performance benchmarking should apply to forecasting models and be enforced equally for reconciliation, anomaly detection, and pre-filing prediction models (Board of Governors of the Federal Reserve System and Office of the Comptroller of the Currency, 2011; Gama et al., 2014).
2. Require explainability (XAI) for any AI output: Whether it is a forecast, control exception, or filing-risk flag, if it has a material impact on financial reporting/forecasting, it must come with documented explainability proportionate to its risk (Arsenault et al., 2024; Bowden et al., 2024).
3. Connect all AI-driven workflows, from predictive modeling to reconciliation and filing preparation, to their corresponding business, ICFR, disclosure controls or SEC disclosure risks (SEC, 2003; COSO, 2013). Document the role of AI in each workflow, including the relevant controls, review responsibilities, and escalation requirements; for generative components, this documentation should follow COSO's 2026 guidance on generative AI (COSO, 2026).
4. Establish IT general controls (ITGCs) over the AI systems: This includes enforcing strict access management, change management for model updates, and active drift monitoring, which lays the groundwork for a governance layer on reporting demands (PCAOB, 2010).
5. Retain human sign-off for exceptions, forecast overrides, and filing certifications. AI should be framed strictly as a tool for triage, drafting, and a first-pass review layer across the entire process (SEC, 2020).
6. Maintain segregation of duties in AI-enabled workflows: Preparer, approver and system administrator roles should remain separate. AI agents should hold least privilege access, should not propose and approve journal entries, and any actions should be logged under unique identities (COSO, 2013).
7. Control generative components: Restrict confidential data shared with third party models, require verification of generated output against source records, and log prompts (COSO, 2026).

8. Conclusion

AI is driving a dual transformation in corporate finance: elevating forecasting while reinforcing data integrity through continuous, automated reconciliation. Combining these may change how organizations manage external reporting risk. By deploying predictive modeling alongside automated controls, organizations may be able to model their disclosures in advance, enabling anomaly detection or misstatement identification before submission, which may reduce risks such as restatements arising from accounting errors, staff comments arising from disclosure review and

filing suspensions. Pursuing these as a unified, integrated implementation agenda offers a coherent view of AI value creation and a common framework for governing model risk, XAI explainability, audit trails, and SEC compliance.

8.1 Opportunities for Future Research

1. Quantifying the impact of reconciliation data quality on downstream forecast accuracy.
2. Comparing case studies across organizations at different levels of the joint maturity model, future research can map out the implementation pathways that frequently yield operational efficiency and robust internal controls.
3. Examining whether explainable AI (XAI) techniques developed for forecasting, such as SHAP and LIME, can be adapted for reconciliation and anomaly detection models. Even though control models face strict auditability demands, they remain less targeted from an explainability standpoint (Arsenault et al., 2024; Bowden et al., 2024).
4. Measuring whether companies that use predictive, controls-driven pre-filing checks receive fewer SEC comment letters or restatements over time than those who still rely on traditional closing and filing processes.
5. Conducting a cost-benefit and risk analysis of deploying a unified AI governance framework for FP&A, controls, financial close, and SEC reporting rather than managing them through siloed governance steps that most organizations use today.

9. AI Usage Declaration

AI tools were used during the preparation of this paper to assist with organization, brainstorming, and language refinement. The authors independently reviewed and evaluated the relevant literature, synthesized the findings, developed the substantive arguments, and verified the accuracy of the paper.

References

- [1] L. Cao (2022). "AI in finance: Challenges, techniques, and opportunities" *ACM Computing Surveys*, vol. 55, no. 3, Art. no. 64, pp. 1-38, 2022. doi: 10.1145/3502289.
- [2] P.D. Arsenault, S. Wang, and J.M. Patenaude (2024). "A survey of explainable artificial intelligence (XAI) in financial time series forecasting" *arXiv preprint arXiv:2407.15909*, 2024. <https://arxiv.org/abs/2407.15909>
- [3] S. Joshi. (2025). "AI and financial model risk management: Applications, challenges, explainability, and future directions" *Preprints.org*, 2025. <https://www.preprints.org/manuscript/202503.2284>
- [4] K.C. Yao, H.C. Hung, C.H. Wang, W.L. Huang, H.T. Liang, T.H. Chu, B.S. Chen, and W.S. Ho (2025). "Application of generative AI in financial risk prediction: Enhancing model accuracy and interpretability" *Information*, vol. 16, no. 10, p. 857, 2025. doi: 10.3390/info16100857.

- [5] D. Saini, B. Jain, N. Ujjwal, P. Sommer, D. R. Mbanga, and D. Mehta (2025). "A unified AI system for data quality control and DataOps management in regulated environments" arXiv preprint arXiv:2512.05559, 2025.
<https://arxiv.org/abs/2512.05559>
- [6] J. Bowden, M. Cummins, D. Dao, and K. Jain (2024). "Explainable AI for Financial Risk Management" University of Strathclyde, Glasgow, U.K., 2024. doi: 10.17868/strath.00089573.
- [7] M. Lokanan and S. Sharma (2025). "Reprint of: The use of machine learning algorithms to predict financial statement fraud" *The British Accounting Review*, vol. 57, no. 1, Art. no. 101560, 2025. doi: 10.1016/j.bar.2025.101560.
- [8] E. Zavitsanos, E. Spyropoulou, G. Giannakopoulos, and G. Paliouras (2025). "Machine Learning for Identifying Risk in Financial Statements: A Survey" *ACM Computing Surveys*, vol. 57, no. 9, Art. no. 220, pp. 1-37, 2025. doi: 10.1145/3723157.
- [9] V. Christophides, V. Efthymiou, T. Palpanas, G. Papadakis, and K. Stefanidis (2020). "An Overview of End-to-End Entity Resolution for Big Data" *ACM Computing Surveys*, vol. 53, no. 6, Art. no. 127, pp. 1-43, 2020. doi: 10.1145/3418896.
- [10] K.C. Moffitt, A.M. Rozario, and M.A. Vasarhelyi (2018). "Robotic process automation for auditing" *Journal of Emerging Technologies in Accounting*, vol. 15, no. 1, pp. 1-10, 2018. doi: 10.2308/jeta-10589.
- [11] Public Company Accounting Oversight Board (PCAOB). "AS 2201: An Audit of Internal Control Over Financial Reporting That Is Integrated with An Audit of Financial Statements". PCAOB Auditing Standards, PCAOB Release No. 2007-005A, Jun. 12, 2007.
<https://pcaobus.org/oversight/standards/auditing-standards/details/AS2201>
- [12] Committee of Sponsoring Organizations of the Treadway Commission (COSO). "Achieving Effective Internal Control Over Generative AI" 2026.
- [13] Public Company Accounting Oversight Board (PCAOB). "AS 2110: Identifying and Assessing Risks of Material Misstatement" PCAOB Auditing Standards, Appendix B, PCAOB Release No. 2010-004, Dec. 2010.
<https://pcaobus.org/oversight/standards/auditing-standards/details/AS2110>
- [14] U.S. Securities and Exchange Commission (SEC). "EDGAR Filer Manual, Volume II: EDGAR Filing" SEC Technical Specifications, Version 69, 17 C.F.R. § 232.301, Mar. 2026.
<https://www.sec.gov/edgar/filerinformation/current-edgar-filer-manual>
- [15] U.S. Securities and Exchange Commission (SEC). "Electronic Signatures in Regulation S-T Rule 302" SEC Release No. 33-10889, 85 Fed. Reg. 82516, Dec. 2020. <https://www.sec.gov/files/rules/final/2020/33-10889.pdf>
- [16] U.S. Securities and Exchange Commission (SEC). "Division of Economic and Risk Analysis (DERA) Risk Assessment: Corporate Issuer Risk Assessment (CIRA) Tool" in Testimony on Continued Oversight of the SEC's Offices and Divisions, Apr. 21, 2016.
<https://www.sec.gov/newsroom/speeches-statements/testimony-04-21-16>

- [17] U.S. Securities and Exchange Commission. "Filing Fee Disclosure and Payment System Modernization" SEC Release No. 33-10997, Washington, DC, USA, 2021.
- [18] Sarbanes-Oxley Act of 2002, Pub. L. No. 107-204, §§ 302, 404, 906, 116 Stat. 745, Jul. 2002.
- [19] U.S. Securities and Exchange Commission, Disclosure Controls and Procedures and Internal Control Over Financial Reporting, 17 C.F.R. §§ 229.307, 229.308, 240.12b-2, 240.13a-14, 240.13a-15, 2003.
- [20] Committee of Sponsoring Organizations of the Treadway Commission (COSO), "Internal Control-Integrated Framework" Executive Summary, Durham, NC, USA, May 2013.
- [21] Board of Governors of the Federal Reserve System and Office of the Comptroller of the Currency, "Supervisory guidance on model risk management" SR Letter 11-7, Apr. 4, 2011.
- [22] J. Gama, I. Žliobaitė, A. Bifet, M. Pechenizkiy, and A. Bouchachia (2014). "A survey on concept drift adaptation" *ACM Comput. Surv.*, vol. 46, no. 4, Art. no. 44, Mar. 2014, doi: 10.1145/2523813.
- [23] C.Y. Harvey Weinstein, L.S. Warnars, K. Christopher Sugianto and R. Tjahyadi, (2026). "Artificial intelligence in the financial industry: A review" in *Proc. 18th Int. Conf. on Knowledge and Smart Technology (KST)*, Pattaya, Thailand, 2026, pp. 287-293, doi: 10.1109/KST67832.2026.11432048.