



The Role of AI-Based Decision Support in Financial Risk Management and Anomaly Detection

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Abstract

This study has examined the role of artificial intelligence-based decision support in financial risk management and anomaly detection within selected United States banking, capital markets, and financial technology contexts. The central problem has been that financial institutions face rising volumes, velocity, and complexity of transactions and exposures, in which fraud, market anomalies, credit deterioration, and operational risk events can develop and propagate faster than conventional rule-based monitoring and periodic manual review can detect them, while stand-alone automation is constrained by opacity, alert fatigue from high false-positive rates, regulatory demands for explainability, and the need for accountable human oversight. The purpose of the study has been to evaluate whether model and data quality integration, anomaly detection accuracy and coverage, explainability, interpretability and transparency, human oversight, trust and governance, and real-time monitoring and scalability significantly improve risk management and performance effectiveness when AI-based decision support is deployed as a collaborative capability rather than as an autonomous black box. A quantitative, cross-sectional, case-based research design has been used, and data have been collected from risk managers, quantitative analysts, fraud and financial-crime specialists, model-risk and compliance officers, and financial data scientists engaged in risk monitoring and decision-making. Out of 277 distributed questionnaires, 236 valid responses have been retained, producing an 85.2% valid response rate. The analysis plan has included descriptive statistics, Cronbach's alpha reliability testing, Pearson correlation analysis, multiple regression modeling, hypothesis testing, a prototype anomaly-detection evaluation, and Python-driven analytical workflow validation. The findings have shown strong agreement across the constructs, with model and data quality integration recording the highest mean score of 4.23, followed by anomaly detection accuracy and coverage at 4.16, explainability, interpretability and transparency at 4.07, risk management and performance effectiveness at 4.02, real-time monitoring and scalability at 3.96, and human oversight, trust and governance at 3.89. Reliability has been confirmed through Cronbach's alpha values ranging from .82 to .91, with overall reliability of .93. Correlation results have shown significant positive relationships between risk management effectiveness and anomaly detection accuracy ($r = .69$), model and data quality integration ($r = .68$), explainability ($r = .64$), human oversight and governance ($r = .60$), and real-time monitoring ($r = .58$), all at $p < .001$. The regression model has been significant, $F(5, 230) = 54.02$, $p < .001$, explaining 54.0% of the variance. The study implies that AI-based decision support can meaningfully strengthen financial risk management and anomaly detection when data quality, detection accuracy, explainability, governed human oversight, and real-time scalability are jointly present.

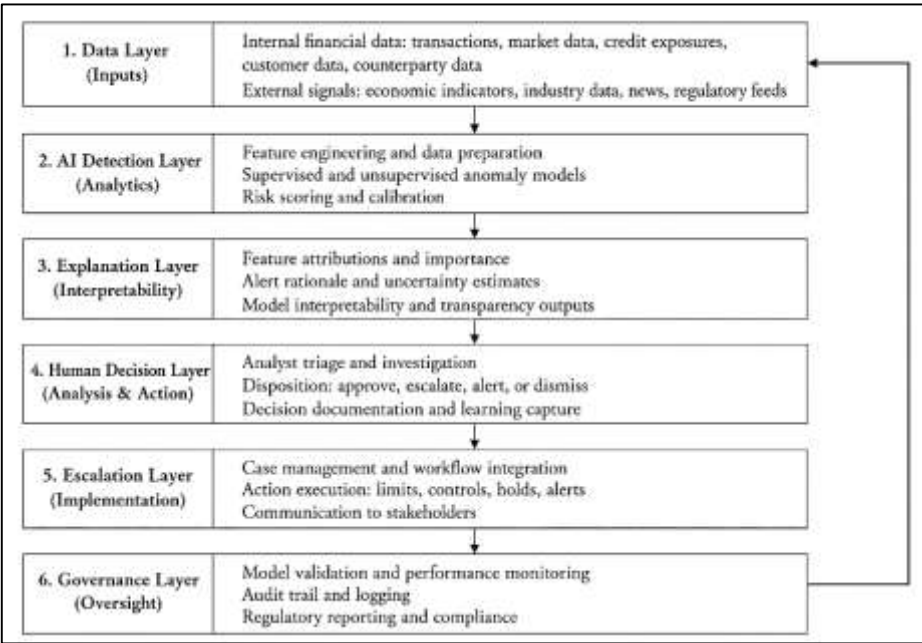
Keywords

Financial Risk Management; Anomaly Detection; AI-Based Decision Support; Explainable AI; Model Risk Governance; Real-Time Monitoring

INTRODUCTION

Financial risk management refers to the identification, measurement, monitoring, and mitigation of the exposures that a financial institution bears, including credit risk, market risk, liquidity risk, operational risk, and the fraud and financial-crime risk that cut across them. Anomaly detection, in this context, refers to the identification of observations, transactions, or patterns that deviate materially from expected behavior in ways that may signal fraud, market abuse, model failure, or emerging loss, and it is a core mechanism through which risk is surfaced before it crystallizes into loss (Chandola et al., 2009). Artificial intelligence-based decision support, as used in this study, refers to machine learning and related systems that ingest heterogeneous financial data, score and flag risk, generate explanations, and present prioritized, interpretable output to a human decision-maker who retains accountability for the action taken, as distinct from fully autonomous systems that act without human review. The object of this study is the decision-support role of such systems, in which the AI and the risk professional operate as a combined capability whose joint output is the unit of risk-management performance, rather than the AI acting as an unaccountable black box or the analyst working without algorithmic assistance. Financial institutions operate in an environment of rising transaction volume, velocity, and interconnection, in which risk events can develop and propagate rapidly across portfolios, counterparties, and markets. Conventional risk monitoring has relied heavily on static rule-based systems and periodic manual review, approaches that struggle with the scale and adaptivity of modern financial activity: rules encode known patterns and are evaded by novel behavior, while manual review cannot keep pace with the data volume (Ngai et al., 2011). Machine learning has been proposed and increasingly adopted to address these limits, and research has demonstrated strong performance of supervised and unsupervised methods for fraud detection, credit-risk modeling, and market-anomaly identification (Bao et al., 2022; Ahmed et al., 2016). Yet the translation of detection performance into risk-management benefit is not automatic, because AI in finance introduces its own challenges, including opacity that conflicts with supervisory expectations, high false-positive rates that create alert fatigue and operational cost, susceptibility to distribution shift as adversaries adapt, and the need for model-risk governance and accountable human oversight (Bussmann et al., 2021). The premise of this study is that the value of AI in financial risk is realized not by replacing the risk professional, nor by leaving the professional without algorithmic support, but by designing the decision-support relationship so that the complementary strengths of machine scale and human judgment are combined under explainability and governance.

Figure 1: AI-Based Decision Support Framework for Financial Risk Management and Anomaly Detection



At the national and international level, the stakes of financial risk management are systemic as well as institutional (Abdur & Iftekhhar, 2021; Hossan, 2021). The global financial crisis demonstrated that failures of risk identification and measurement can propagate across institutions and into the real economy, and it prompted a wave of regulation emphasizing robust risk management, model governance, and supervisory transparency (Committee, 2011). Financial-crime losses, fraud, and market abuse impose large and growing costs, and institutions face simultaneous pressure to detect more while generating fewer false alarms and to demonstrate to regulators that their models are explainable, validated, and governed. Research on AI in finance has emphasized that the benefit of these systems depends not only on raw predictive accuracy but on explainability, on the calibration of human trust and reliance, and on the governance that keeps models valid over time (Arner et al., 2017; Buchanan, 2019). This evidence is directly relevant to financial risk because the domain is characterized by adversarial adaptation, heavy regulation, and severe consequences of both missed risks and excessive false positives, precisely the conditions under which the design of the human-AI decision-support relationship most strongly determines whether AI helps or harms (Amir & Chapal, 2022; Hasan & Uddin, 2022). The national significance of this study is therefore connected to the need for an integrated account of the conditions, including data quality, detection accuracy, explainability, oversight and governance, and real-time scalability, under which AI-based decision support strengthens rather than merely complicates financial risk management (Shurovi & Hossain, 2022; Mohiul & Badrul, 2022).

The background and motivation of this study have been shaped by the rapid emergence of AI and advanced analytics within financial services. Risk monitoring has moved beyond static rules because institutions increasingly require systems that integrate heterogeneous data, detect novel and evolving anomalies, explain their reasoning to analysts and regulators, operate in real time at scale, and remain under governed human oversight. Analytics capability research has shown that data-driven capability improves performance when organizations combine data resources, technological infrastructure, and process-oriented use (Gupta & George, 2016). Predictive and prescriptive modeling have been recognized as complementary components of applied analytics research, because risk systems must both describe observed patterns and inform actions that affect exposure and loss (Shmueli & Koppius, 2011). This reasoning supports the present study because the research design includes descriptive statistics, correlation analysis, regression modeling, and a prototype anomaly-detection evaluation. Python-based scientific computing tools have been shown to support the numerical processing, data analysis, and evaluation workflows that data-driven financial research requires (Harris et al., 2020; Virtanen et al., 2020).

The problem statement of this study has been grounded in a persistent operational gap. Conventional financial risk monitoring has relied on static rule-based systems whose fixed thresholds are known to adversaries and evaded by novel patterns, and on periodic manual review whose capacity is bounded and cannot scale to modern data volume, so that a meaningful fraction of fraud and emerging risk is detected late or not at all (Kanti & Rony, 2022; Sadia et al., 2022). The introduction of stand-alone machine learning has not by itself resolved this gap, because a model that is accurate on historical data may degrade silently as behavior shifts, because an opaque score that analysts and regulators cannot interrogate invites either over-reliance or rejection and fails supervisory expectations, and because detection systems that generate high false-positive rates impose alert fatigue and operational cost that can erode rather than improve net risk outcomes (Bussmann et al., 2021). Moreover, an AI system deployed without model-risk governance and accountable human oversight is itself a source of model risk, and one that operates without real-time scalability cannot detect fast-moving anomalies in time to act (Golam & Amir, 2023; Badrul & Mominul, 2023). The combination of evadable rules, bounded manual capacity, opaque and drifting models, false-positive burden, and ungoverned deployment has created a situation in which neither rules alone, nor analysts alone, nor autonomous AI reliably minimizes financial risk (Hossan & Adar, 2023; Risha & Khalid, 2023). This study has addressed that gap by proposing and empirically evaluating an AI-based decision-support framework in which detection accuracy, explainability, governed human oversight, and real-time scalability are combined. The purpose of this study has been to develop and validate a framework for the role of AI-based decision support in financial risk management and anomaly detection (Amir, 2024; Sadia & Binayan,

2023). The framework has treated model and data quality integration as the informational foundation, anomaly detection accuracy and coverage as the core detection capability, explainability, interpretability and transparency as the interface through which the AI contribution becomes verifiable and supervisable, human oversight, trust and governance as the mechanism that keeps decisions accountable and models valid, and real-time monitoring and scalability as the condition under which detection is timely and operationally feasible, with the risk professional as the accountable decision-maker whose judgment integrates the AI contribution (Hossan, 2024; Sadia & Md, 2024). The study objectives have been formulated as follows. The first objective has examined the role of model and data quality integration in supporting accurate, context-aware risk detection. The second objective has examined the role of anomaly detection accuracy and coverage in surfacing fraud, market anomalies, and emerging loss (Hossain, 2024; Shima Ali et al., 2024). The third objective has examined the role of explainability, interpretability and transparency in supporting verifiable and supervisable decisions. The fourth objective has examined the role of human oversight, trust and governance in producing accountable and valid model use. The fifth objective has examined the role of real-time monitoring and scalability in enabling timely detection at scale (Amir, 2025; Zaman, 2024). The sixth objective has validated the integrated framework by testing whether the combined components significantly explain variation in risk management and performance effectiveness (Arif Uz et al., 2025; Hossan, 2025). The significance of this study has extended across academic, industry, and policy dimensions. Academically, the study has contributed by connecting several research streams that have developed largely in parallel: machine learning for finance, anomaly detection, explainable AI, human-AI decision-making and trust, information systems success theory, and model-risk governance. By integrating these within a single measurable framework, the study has offered a structure in which data quality, detection accuracy, explainability, oversight, and scalability are treated as complementary requirements rather than isolated concerns. For industry, the study has offered financial institutions a structured way to evaluate whether their AI risk investments are producing genuine risk-management benefit, because the framework identifies the specific conditions that must be present before decision support improves rather than merely complicates risk outcomes. Policy-wise, the study has aligned with supervisory priorities for sound model risk management, explainability, and accountable use of AI in finance, because the outcomes of the framework include earlier and more accurate detection, fewer false alarms, reduced losses, and demonstrable governance, all of which strengthen the safety and soundness of financial institutions and the stability of the system in which they operate.

LITERATURE REVIEW

The literature review of this study has been organized to build a cumulative foundation for the proposed AI-based decision-support framework. It has begun with financial risk management and its limits, moved through machine learning and anomaly detection in finance, examined the trajectory from classical models toward deep and representation learning, examined explainability and interpretability, addressed human-AI decision-making and trust, considered model-risk governance and regulation, situated the framework within the emerging regulatory-technology and systemic-risk literature, reviewed the information systems and capability theories that underpin the framework, and concluded by identifying the research gap the study has addressed. Throughout, the review has maintained the position that risk-management benefit is not reducible to detection accuracy alone, because the realized value of an AI risk system depends jointly on the quality of the data it integrates, the accuracy and coverage of the anomalies it surfaces, the explainability that makes its output verifiable and supervisable, the governed human oversight that keeps decisions accountable, and the real-time scalability that makes detection timely. The review proceeds from the problem the framework addresses, through the technical means available to address it, to the human, organizational, and regulatory conditions under which those means produce genuine benefit, so that each construct in the conceptual model is anchored in a distinct and well-developed body of prior work.

Financial risk management and the limits of conventional monitoring

The foundational premise of this study is that financial risk management is consequential and only partially served by conventional monitoring. Risk management has been formalized around the measurement and control of credit, market, liquidity, and operational exposures, with quantitative measures such as value at risk and expected shortfall used to summarize potential loss (Jorion, 2007). The global financial crisis exposed the limits of risk measurement that relied on narrow assumptions and backward-looking data, and it prompted regulatory reform emphasizing robust, forward-looking, and well-governed risk management (Basel Committee, 2011). In the operational and financial-crime domain, conventional detection has relied on rule-based transaction monitoring whose fixed thresholds are known to be evaded and whose high false-positive rates impose large investigation costs (Ngai et al., 2011).

The taxonomy of financial risk that this literature has produced is itself relevant to the framework, because different risk categories present different detection problems. Credit risk unfolds slowly and is dominated by the estimation of default probability and loss given default, for which scoring models have a long history extending from discriminant analysis and logistic regression to modern machine learning (Ngai et al., 2011). Market risk is dominated by the estimation of potential loss over short horizons, for which value-at-risk and expected-shortfall models remain the supervisory standard despite their well-documented sensitivity to distributional assumptions and their tendency to understate tail risk in stressed conditions (Jorion, 2007). Operational and financial-crime risk, by contrast, is dominated by the detection of rare, adversarially generated events within enormous streams of ordinary activity, and it is here that the mismatch between conventional monitoring and the scale of modern finance is most acute (Kanti, 2025; Shima Ali et al., 2025). This heterogeneity matters for the present study because a single detection technology cannot be equally suited to every risk category, and the framework therefore treats anomaly detection accuracy and coverage as a construct that must span multiple risk types rather than optimize a single one, an emphasis reflected in the coverage dimension of the measurement instrument (Amir, 2026; Mahmudul & Sadia, 2026).

Figure 2: Categories of Financial Risk and Points of AI-Based Detection

Financial Risk Category	Key Data Sources	AI Detection Methods	Points of AI-Based Detection	Human Investigation Intersection
Credit Risk Default and credit deterioration	• Loan & KYC data • Credit scores • Payment history	• Credit scoring • PD models • Early warning analytics	• Deteriorating credit metrics • Repayment anomalies	• Review high-risk alerts • Validate decision
Market Risk Adverse price, rate, and index movements	• Price-volume data • Yield curves • FX & market indices	• Time-series forecasting • Volatility models • Regime detection	• Abnormal price/volume shifts • Volatility spikes	• Assess market events • Adjust positions
Liquidity Risk Insufficient liquidity to meet obligations	• Cash flow data • Deposit-withdrawal data • Funding profiles	• Liquidity forecasting • Stress testing • Anomaly detection	• Withdrawal surges • Coverage breaches	• Review liquidity alerts • Choose mitigation actions
Operational Risk Process, system, or people failures	• System logs • Incident data • Workflow records	• Process mining • Failure prediction • Text analytics	• Process deviations • Control failures	• Investigate root causes • Implement corrective action
Fraud & Financial Crime Risk Fraud, AML, and sanctions risk	• Transaction monitoring • Customer behavior • Watchlists	• Anomaly detection • Behavioral analytics • AML risk scoring	• Suspicious transaction patterns • High-risk links	• Investigate alerts • Escalate to compliance

A further strand of this literature concerns the organizational and behavioral limits of conventional monitoring, which are distinct from its technical limits. Even where rules and periodic review are technically adequate, the volume of alerts they generate can overwhelm the human capacity to investigate, producing a backlog in which genuine risks are buried among false positives and dispositioned late or not at all (West & Bhattacharya, 2016). This alert-fatigue problem is not solved by generating more alerts, and it explains why the literature has increasingly framed the objective of detection not as maximizing sensitivity but as improving the precision-recall frontier, so that analyst attention is directed to the alerts most likely to be genuine (Hossan, 2026; Shurovi, 2026). The present framework inherits this framing directly, measuring risk-management effectiveness through a construct that explicitly includes false-alarm reduction and analyst efficiency alongside loss avoidance, on the theoretical ground that a detection system which improves recall while degrading precision may reduce rather than increase realized risk-management performance once investigation capacity is accounted for (Sadia, 2026; Shima Ali et al., 2026).

Machine learning and anomaly detection in finance

Machine learning has been applied across financial risk with increasing sophistication. Anomaly detection, as a general problem, has been surveyed extensively, distinguishing supervised, semi-supervised, and unsupervised approaches and the characteristic challenge that anomalies are rare, evolving, and context-dependent (Chandola et al., 2009; Ahmed et al., 2016). In finance specifically, machine learning has been applied to fraud detection, credit scoring, anti-money-laundering, and market surveillance, with studies reporting substantial improvements over rule-based baselines in both detection rate and false-positive reduction (Bao et al., 2022; West & Bhattacharya, 2016).

A critical lesson from this literature is the severe class imbalance and adversarial adaptation that characterize financial anomaly detection: fraud is rare, so accuracy is a misleading metric, and adversaries adapt to detection, so models degrade unless retrained. This has focused evaluation on precision, recall, and the precision-recall trade-off rather than raw accuracy, and it has emphasized the importance of data quality, feature engineering, and continuous monitoring for drift (Dal Pozzolo et al., 2018). This is directly relevant to the present study because it establishes that model and data quality integration and detection accuracy and coverage are distinct and both essential, and that the evaluation of detection must use the precision-recall framing that the prototype in this study adopts.

The methodological literature on anomaly detection has clarified that the choice among supervised, semi-supervised, and unsupervised approaches is itself consequential for financial application. Supervised methods, which learn from labeled examples of past fraud or loss, achieve high precision on known patterns but are structurally blind to novel behavior for which no labels exist, and they inherit whatever biases and gaps the labeling process contains (Chandola et al., 2009). Unsupervised and semi-supervised methods, which flag deviations from a learned model of normal behavior, can surface previously unseen anomalies but tend to generate more false positives because not every deviation is malicious (Syed Nurul, 2026). The practical consequence, well documented in the fraud literature, is that operational systems increasingly combine the two, using unsupervised detection to widen coverage and supervised scoring to sharpen precision (Ahmed et al., 2016). This hybrid architecture is precisely what the anomaly detection accuracy and coverage construct is intended to capture, since coverage speaks to the unsupervised breadth of the system and accuracy to its supervised sharpness, and the framework treats them as jointly necessary rather than substitutable.

The literature has also increasingly emphasized that the binding constraint on financial anomaly detection is frequently the data rather than the algorithm. Label scarcity, label delay, since a transaction may not be confirmed as fraudulent for weeks, concept drift as behavior evolves, and the fragmentation of relevant signals across systems that were never designed to interoperate all degrade detection independently of model choice (Dal Pozzolo et al., 2018; Bao et al., 2022). Studies that have decomposed the sources of detection performance have repeatedly found that improvements in feature engineering and data integration yield gains comparable to or exceeding those from more sophisticated model classes, a finding that directly motivates the elevation of model and data quality integration to a first-order construct and anticipates the empirical result, reported later, that this construct is the strongest single predictor of risk-management effectiveness.

From classical models to deep and representation learning

A distinct and rapidly growing strand of the literature concerns the migration of financial detection from classical statistical and tree-based models toward deep learning and representation learning. Deep neural networks, which learn hierarchical feature representations directly from raw or minimally engineered inputs, have been applied to fraud detection, credit modeling, and market surveillance, and have shown particular promise where the relevant structure is sequential or relational rather than tabular (Bao et al., 2022). Recurrent and sequence models capture the temporal patterns of transaction streams, autoencoders and other reconstruction-based methods flag anomalies as inputs the model cannot reconstruct well, and graph-based methods represent accounts and counterparties as nodes in a network so that coordinated fraud rings, invisible to transaction-level models, become detectable as anomalous subgraphs. These approaches extend the coverage of detection into structures that classical models cannot represent.

The literature is equally clear, however, that the migration to deep learning intensifies rather than resolves the framework’s central tensions. More expressive models are more data-hungry and therefore more sensitive to the label scarcity and drift that characterize financial anomalies; they are more opaque and therefore harder to explain to analysts, validators, and supervisors; and they are more prone to overfitting spurious structure that fails under adversarial adaptation (Guidotti et al., 2018; Bracke et al., 2019). This tension is theoretically important for the present study because it means that raw model capability and realized risk-management benefit can diverge: a more powerful detector that cannot be explained or governed may be less deployable, and therefore less valuable in practice, than a simpler one that can. The framework encodes this insight by refusing to treat detection accuracy as the sole determinant of effectiveness and by placing explainability, oversight, and governance alongside it, so that the empirical model can test whether the conditions that make powerful models usable contribute to effectiveness over and above the detection capability itself.

Figure 3: Evolution of Detection Methods from Rule-Based Systems to Representation Learning

	1. Rule-Based Systems 1990s–early 2000s	2. Classical Machine Learning Early–mid 2000s	3. Ensemble & Gradient Boosted Models Mid 2010s	4. Deep & Graph Representation Learning Late 2010s–2020s
Core Approach	Expert-defined rules and thresholds	Statistical and machine learning on engineered features	Combine multiple weak learners for better accuracy	Learn rich representations directly from complex data
Typical Techniques	If–Then rules, thresholds, scorecards	Logistic regression, decision trees, SVM, Naive Bayes	Random forest, XGBoost, LightGBM, CatBoost	Deep neural networks (RNN, CNN, Autoencoders), GNN
Data Utilization	Structured internal transaction data	Structured data with engineered features	Structured + semi-structured data with many features	Structured, unstructured, relational, and network data
Detection Strength	Detect known patterns, limited adaptability	Detect complex (linear/nonlinear) patterns	High predictive power, capture nonlinear interactions	Capture complex, temporal and relational anomalies
Explainability	High (rules are easy to interpret)	Moderate (feature importance, coefficients)	Moderate (SHAP, feature importance)	Lower (requires XAI techniques)
Governance	Simple validation, easy documentation	Model validation, monitoring required	Robust validation, bias and overfitting control	Strong governance, transparency essential
Increasing Coverage, Accuracy, and Expressive Power				

Explainability, interpretability, and transparency

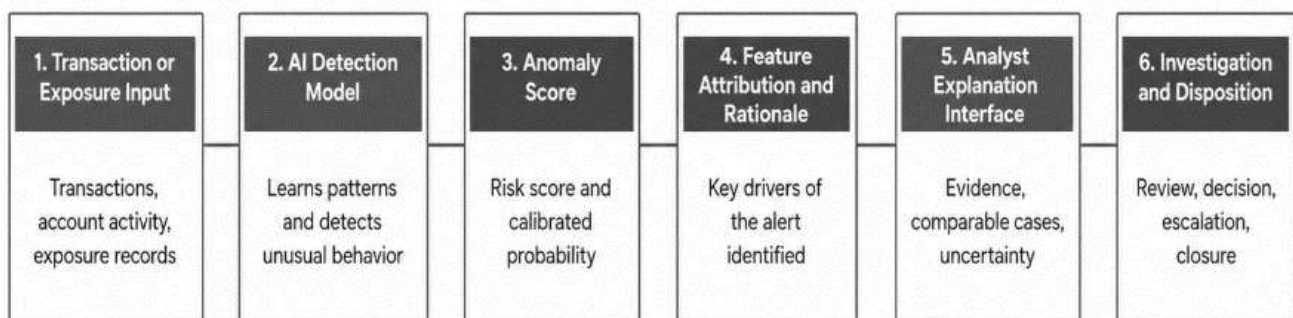
The explainability of AI risk models has become a central concern, both because opaque models are difficult to trust and validate and because financial regulation increasingly expects institutions to explain automated decisions. Research on explainable AI has developed methods for attributing model outputs to input features and for producing human-interpretable rationales, and has argued that explainability is a precondition for the responsible deployment of AI in high-stakes domains (Guidotti

et al., 2018; Busmann et al., 2021). In credit and fraud, explainability supports the analyst's investigation by indicating why an alert was raised, supports the customer's right to an explanation of adverse decisions, and supports the validator's and regulator's assessment of whether the model is sound and non-discriminatory.

The explainability literature has also drawn a distinction, important for financial application, between models that are intrinsically interpretable and complex models rendered interpretable through post-hoc explanation. Intrinsically interpretable models, such as scorecards and shallow trees, offer transparency by construction but may sacrifice detection power, while post-hoc methods attach feature-attribution or surrogate explanations to an opaque model, offering higher potential accuracy at the cost of explanations that approximate rather than reveal the model's true reasoning (Guidotti et al., 2018). This distinction has generated a substantive debate about whether post-hoc explanations are adequate for high-stakes decisions, since an explanation that is faithful to the model but not to the underlying reality, or faithful to neither, can create an illusion of understanding that is worse than acknowledged opacity. In the financial context this debate is not academic, because supervisory expectations increasingly require that institutions be able to justify automated decisions to customers and regulators, and an explanation that cannot withstand scrutiny exposes the institution to legal and reputational risk (Bracke et al., 2019).

This literature grounds the explainability, interpretability, and transparency construct. It establishes that explanation is not a cosmetic addition but a functional requirement: an alert that the analyst cannot interrogate cannot be efficiently investigated, a model that the validator cannot interpret cannot be properly governed, and an automated decision that cannot be explained may not be permissible. It further establishes that explainability serves at least three distinct audiences with distinct needs, the analyst who must investigate an alert, the validator and risk manager who must assess the model's soundness, and the customer and regulator who are entitled to understand an adverse decision, and that a system may serve one audience well while failing another. The present study therefore treats explainability as a measured, multidimensional determinant of risk-management effectiveness rather than as a compliance formality, consistent with the position that verifiable and supervisable output is what converts detection into accountable action across all three audiences.

Figure 4: Explainable AI Pipeline for Financial Anomaly Alerts



Human-AI decision-making and trust in finance

The decisive determinant of whether AI improves risk outcomes is the quality of the decision-making relationship between the risk professional and the system. Research on human-AI decision-making has shown that the effect of algorithmic advice depends on whether the human can appropriately calibrate reliance to the system's reliability, and that both over-reliance, which propagates model errors, and under-reliance, which discards correct signals, degrade joint performance (Lee & See, 2004). In finance, this manifests as the analyst's decision to investigate, escalate, or dismiss an alert, and as the risk committee's decision to rely on a model output, both of which depend on calibrated trust supported by explanation and demonstrated performance.

The human-factors literature has documented specific mechanisms through which the human-AI relationship in risk work can fail, and these mechanisms have direct design implications. Automation bias, the tendency to accept automated output without adequate scrutiny, is amplified under time pressure and high workload, precisely the conditions of frontline risk investigation, and it causes

analysts to inherit model errors they might otherwise have caught (Parasuraman & Riley, 1997). Its mirror image, algorithm aversion, causes decision-makers to discount algorithmic advice after observing it err, even when the algorithm remains more reliable than their unaided judgment, so that a single visible failure can trigger disproportionate and costly disuse. Both failure modes are governed by trust that is miscalibrated to true reliability, and the literature establishes that calibration is supported by transparency about when and why the system is likely to be right or wrong, which links the trust construct tightly to the explainability construct (Lee & See, 2004).

This literature is the direct foundation for the human oversight, trust and governance construct. It establishes that trust is calibrated rather than fixed, that explanation and demonstrated reliability are its antecedents, and that the outcome of interest is the performance of the human-AI system rather than the model in isolation, which is why the present study measures risk-management effectiveness at the level of the decision-support relationship and evaluates the prototype against rule-based and classical baselines to isolate the contribution of AI-based support. It also connects to governance because accountable oversight is the organizational mechanism through which appropriate reliance is institutionalized and model risk is controlled: individual analysts calibrate trust case by case, but only governance structures, through validation, monitoring, and escalation procedures, ensure that appropriate reliance is sustained across the institution and over time rather than left to individual disposition.

Model-risk governance and regulation

The final stream of literature concerns the governance conditions under which AI risk models can be deployed soundly. Supervisory guidance on model risk management has established that models are themselves a source of risk and must be subject to development standards, independent validation, ongoing monitoring, and governance across their lifecycle (Federal Reserve & OCC, 2011). Applied to AI, this literature emphasizes that machine learning models pose heightened governance challenges because of their complexity, their dependence on data that may drift or embed bias, and their opacity, and that transparency, monitoring, and human accountability are necessary conditions for safe use (Bracke et al., 2019).

The governance literature has increasingly distinguished the model-risk challenges specific to machine learning from those of traditional statistical models, and this distinction sharpens the framework. Traditional model-risk management assumes models that are relatively stable, interpretable, and validated at discrete intervals, whereas machine learning models retrain on shifting data, resist interpretation, and can degrade continuously between validation cycles, so that periodic validation is insufficient and continuous monitoring becomes necessary (Bracke et al., 2019). The literature has also emphasized that the data dependence of machine learning imports a new category of risk, since a model can be individually sound yet embed the biases, gaps, and drift of the data it learned from, which is why data governance and model governance are increasingly treated as inseparable. This reinforces the framework's coupling of model and data quality integration with human oversight, trust and governance, since the same data deficiencies that degrade detection also create the governance exposures that oversight must catch.

This literature grounds the governance dimension of the framework. It establishes that governance is partly constitutive of risk-management performance, because an ungoverned model that drifts or embeds bias produces risk rather than reducing it, and because validation and monitoring are the mechanisms through which the silent degradation of financial models is caught before it causes loss. It also connects governance to fairness, since credit and fraud models that perform unevenly across customer groups can produce discriminatory outcomes with legal and reputational consequences (Kleinberg et al., 2018). The present study therefore treats human oversight, trust and governance as a measured determinant of risk-management effectiveness rather than as an external constraint, consistent with the position that sound AI-based risk management requires the model, the professional, and the governance layer to operate together.

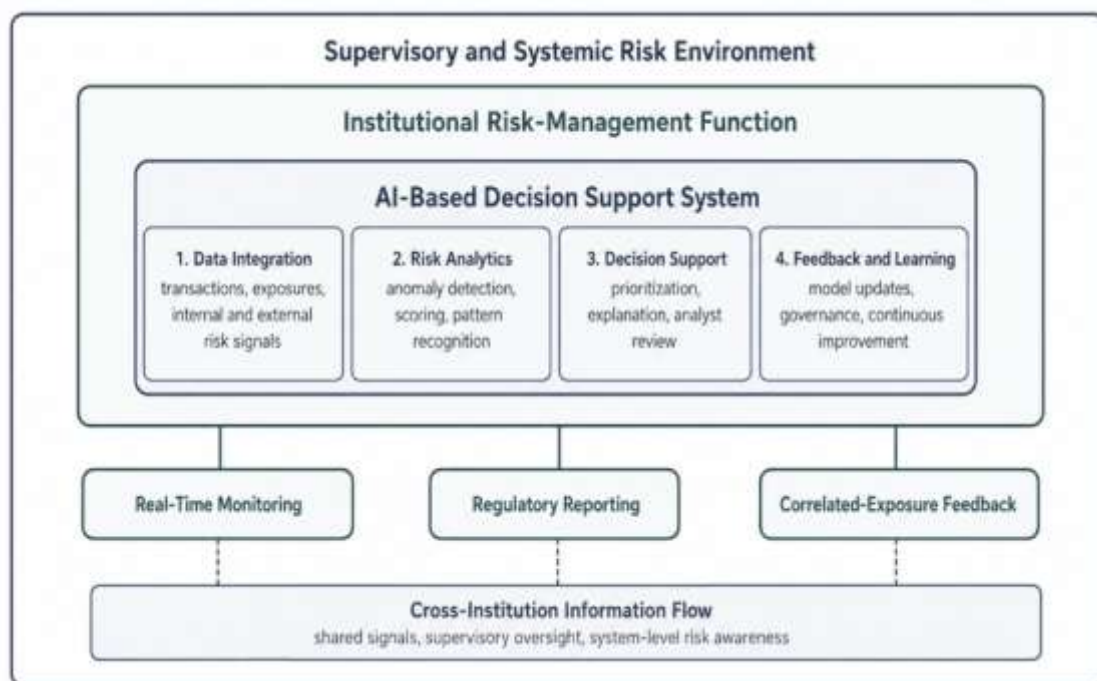
Regulatory technology, real-time monitoring, and systemic risk

A final and increasingly prominent stream of the literature situates AI-based risk management within the broader movement toward regulatory technology and real-time supervision. The regulatory-technology literature has argued that the same advances that enable adaptive detection also enable a

shift from periodic, backward-looking compliance toward continuous, forward-looking monitoring, in which risk and compliance signals are computed in near real time rather than reconstructed after the fact (Arner et al., 2017; Buchanan, 2019). This shift is directly relevant to the real-time monitoring and scalability construct, because the value of a detection signal in fast-moving fraud and market contexts decays rapidly with latency, so that a technically accurate detection that arrives after a loss has crystallized delivers little of its potential benefit. The literature thus establishes timeliness and scale not as engineering conveniences but as determinants of whether detection translates into prevention, which is the theoretical basis for treating real-time monitoring and scalability as a measured determinant of effectiveness rather than an implementation detail.

The systemic-risk literature adds a further dimension by observing that the widespread adoption of similar AI models across institutions can create new correlated exposures even as it reduces idiosyncratic risk at each institution. If many institutions rely on similar models trained on similar data, they may respond to market signals in correlated ways, amplifying rather than dampening instability, and shared model blind spots may leave the system collectively exposed to the same unseen risks (Buchanan, 2019). This literature connects the institutional focus of the present framework to its systemic context and reinforces the emphasis on governance and human oversight, since a system-wide reliance on automated detection without accountable human judgment could propagate correlated errors at scale. While the present study measures effectiveness at the institutional level, this literature motivates the framework's insistence that AI functions as governed decision support rather than autonomous action, on the theoretical ground that accountable human oversight is a safeguard not only for the individual institution but for the stability of the system in which it participates.

Figure 5: AI-Based Decision Support Within the Institutional and Systemic Risk Environment



Synthesis of the reviewed literature

Taken together, the reviewed literature supports a single cumulative argument that the conceptual framework of this study formalizes. The financial risk management literature establishes that conventional monitoring is outpaced by the scale, velocity, and adversarial adaptation of modern finance, creating the need the framework addresses. The machine learning and anomaly detection literature establishes that adaptive detection can meet this need but only under the correct evaluation metrics for rare, imbalanced events, and that data quality is frequently the binding constraint, grounding the model and data quality integration and anomaly detection accuracy and coverage constructs. The literature on the migration to deep and representation learning establishes that greater

model power intensifies rather than resolves the tensions of opacity, data dependence, and governance, so that raw capability and realized benefit can diverge. The explainability literature establishes that verifiable, audience-appropriate explanation is a functional precondition for investigation, validation, and supervision, grounding the explainability construct. The human-AI decision-making literature establishes that calibrated reliance mediates the conversion of model accuracy into decision accuracy, and the model-risk governance and regulatory-technology literatures establish that accountable oversight, continuous monitoring, and real-time scalability are constitutive of sustained effectiveness rather than external to it, grounding the human oversight, trust and governance and real-time monitoring and scalability constructs. Across all six streams, the recurring theme is that detection accuracy is necessary but not sufficient, and that the realized value of AI-based decision support is jointly determined by the informational, detection, explanatory, behavioral, governance, and infrastructural conditions under which it operates. This theme is the organizing premise of the theoretical foundation and the conceptual framework that follow.

Theoretical foundation of the study

The conceptual architecture of this study has been grounded in five established theoretical perspectives, each of which explains a distinct causal mechanism through which AI-based decision support is converted into risk-management effectiveness. No single theory is sufficient. Decision theory under uncertainty defines the structure of the risk decision; signal detection theory defines the detection trade-off; trust-in-automation theory defines appropriate reliance; information systems success and task-technology fit define the conversion of capability into benefit; and agency and governance theory define the accountability constraint. The five theories have been integrated into a single layered structure, presented in the order in which they operate within the causal chain.

Theory 1: Decision Theory and Expected Utility under Uncertainty (von Neumann & Morgenstern, 1944; Savage, 1954)

The formal foundation of the risk decision is provided by decision theory, which models choice under uncertainty as the maximization of expected utility over outcomes weighted by their probabilities (Neumann & Morgenstern, 1944; Savage, 1954). Applied to financial risk, this theory frames every alert disposition, exposure decision, and mitigation action as a choice whose value depends on the probability of the risk event and the costs of the possible errors, so that the decision-maker who has better probability estimates and better-calibrated information makes better decisions. The theoretical significance is that it locates the value of AI-based decision support in the improvement of the probability estimates and the information on which risk decisions are based: a system that produces more accurate, better-calibrated risk scores improves expected-utility decisions even when the human makes the final choice. This justifies operationalizing the dependent construct as risk-management effectiveness measured across loss avoidance, detection, and efficiency, and it grounds the treatment of model and data quality integration as the foundation, since the quality of probability estimates is bounded by the quality of the data and models that produce them.

Theory 2: Signal Detection Theory and the Detection Trade-off (Green & Swets, 1966; Swets et al., 2000)

The structure of the detection problem is provided by signal detection theory, which models the detection of a rare event, such as fraud or an emerging loss, as the discrimination of signal from noise under uncertainty, and separates discriminability from the decision threshold that trades false negatives against false positives (Green & Swets, 1966; Swets et al., 2000). In financial anomaly detection, this theory is directly operative because the central operational tension is between catching more true anomalies and generating more false alerts, and because the extreme class imbalance of fraud makes the precision-recall trade-off, rather than raw accuracy, the meaningful description of performance. The theory predicts that genuine improvement comes from increased discriminability, detecting more true anomalies at the same false-alarm rate, rather than from moving the threshold, and this prediction motivates the anomaly detection accuracy and coverage construct and grounds the prototype evaluation in precision-recall comparison across methods.

Theory 3: Trust in Automation and Appropriate Reliance (Lee & See, 2004; Parasuraman & Riley, 1997)

The behavioral mechanism that governs whether decision support improves outcomes is supplied by trust-in-automation theory, which establishes that human reliance on automation is mediated by trust, that trust should be calibrated to the automation's true reliability, and that miscalibration in either direction degrades joint performance (Lee & See, 2004; Parasuraman & Riley, 1997). In financial risk, over-trust produces automation bias, in which the analyst accepts an incorrect model output and inherits its error, while under-trust produces disuse, in which the analyst disregards a correct alert amid alert fatigue and forfeits its benefit. The theory identifies the antecedents of calibrated trust as demonstrated performance, process transparency, and clarity of purpose, which maps precisely onto the framework's emphasis on explainability and governance. This theory is indispensable because it explains why detection accuracy is not sufficient: the benefit of an accurate system is realized only when the analyst's reliance is calibrated to it, which is exactly what the human oversight and trust dimension captures.

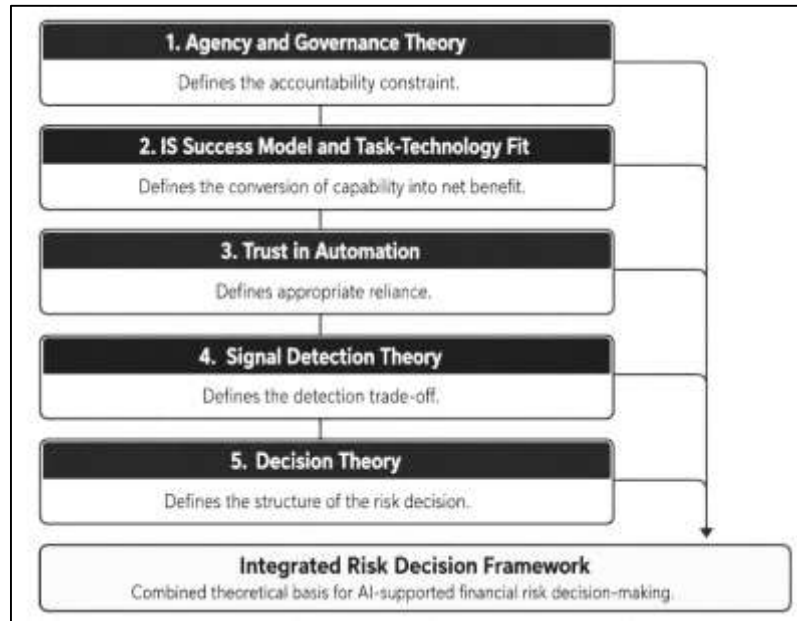
Theory 4: Information Systems Success and Task-Technology Fit (DeLone & McLean, 2003; Goodhue & Thompson, 1995)

The organizing theory that binds the technical constructs to the risk outcome is the Information Systems Success Model, which posits that net benefit depends on system quality and information quality operating through use and user satisfaction (DeLone & McLean, 2003). Mapped onto the framework, anomaly detection accuracy and explainability correspond to system quality, model and data quality integration corresponds to information quality, real-time monitoring and governance correspond to service and functional quality dimensions, and risk management effectiveness corresponds to net benefits. Task-Technology Fit theory complements this by holding that performance improves only when the capabilities of a technology match the demands of the task (Goodhue & Thompson, 1995). In the risk context, this predicts that a capable detection system produces benefit only when its outputs fit the analyst's investigation task and the institution's decision workflow, and that a mismatch, such as unexplained alerts or latency too high for timely action, will suppress benefit regardless of underlying accuracy. Together these theories predict that information quality is coordinate with system quality and that fit and trust mediate the conversion of capability into risk-management effectiveness.

Theory 5: Agency, Accountability, and Governance Theory (Jensen & Meckling, 1976; Eisenhardt, 1989)

The accountability constraint on the outcome is supplied by agency and governance theory, which analyzes the delegation of decision authority to an agent, here an automated model, and the mechanisms of monitoring, control, and accountability required to align the agent's behavior with the principal's objectives (Jensen & Meckling, 1976; Eisenhardt, 1989). Applied to AI-based risk decision support, this theory frames the model as an agent to which detection and scoring are delegated, and it holds that this delegation creates risk unless accompanied by validation, monitoring, and human accountability, because an unmonitored agent may pursue proxies that diverge from the institution's true objective, as when a model optimizes a biased label or drifts from the current risk environment. The theory is indispensable because it reframes governance from external compliance into a determinant of the true risk outcome: the relevant measure of effectiveness is risk reduction that is accountable, validated, and aligned with institutional and regulatory objectives. This directly grounds the human oversight, trust and governance construct and predicts that governance, by aligning the model with institutional objectives and catching its failures, contributes to realized and sustainable risk-management effectiveness.

Figure 6: Integrated Theoretical Framework of the Study



Theoretical synthesis and construct derivation

The five theories converge on a single integrated proposition. Decision Theory establishes that the value of decision support lies in improving the probability estimates and information on which risk decisions rest, predicting that model and data quality integration is foundational. Signal Detection Theory establishes that genuine detection improvement is increased discriminability rather than threshold movement, predicting that anomaly detection accuracy and coverage contributes through the precision-recall frontier rather than raw accuracy. Trust in Automation establishes that calibrated reliance mediates the conversion of model accuracy into decision accuracy, predicting that oversight and trust are necessary for benefit. The IS Success Model and Task-Technology Fit establish that information quality is coordinate with system quality and that fit mediates benefit, predicting that data quality and detection accuracy dominate downstream factors. Agency and Governance Theory establishes that the true outcome is accountable and aligned risk reduction, predicting that governance contributes to realized and sustainable effectiveness.

Each of the five independent constructs has therefore been derived from theory rather than selected inductively. Model and data quality integration operationalizes information quality in the IS Success Model and the informational basis of expected-utility decisions. Anomaly detection accuracy and coverage operationalizes system quality and the discriminability of signal detection theory. Explainability, interpretability and transparency operationalizes the verifiability that supports both appropriate reliance and governance. Human oversight, trust and governance operationalizes the appropriate-reliance mechanism of trust-in-automation theory and the accountability mechanism of agency theory. Real-time monitoring and scalability operationalizes the technical and service-quality condition for timely detection. The dependent construct operationalizes net benefits in the IS Success Model and improved expected-utility risk outcomes in decision theory. This derivation ensures that the empirical model tested here is a test of theory rather than an exploration of correlations.

Research gap

Synthesis of the reviewed literature has revealed a specific gap. The financial risk management literature has established the limits of conventional monitoring but has not, in general, been connected to the concrete design of AI decision support that could address them. The machine learning and anomaly detection literature has demonstrated strong detection performance but has emphasized model metrics over realized risk-management benefit and has often evaluated models in isolation from the analyst and governance context in which they operate. The explainable AI literature has developed powerful methods but has seldom been evaluated as a measured determinant of risk outcomes in operational settings. The human-AI decision-making literature has established that reliance must be

calibrated but has rarely been applied to financial risk decision-making on heterogeneous data. The model-risk governance literature has established that governance is necessary but has seldom been treated as a measured determinant of detection and risk performance. No prior study identified in this review has integrated model and data quality, detection accuracy and coverage, explainability, human oversight and governance, and real-time scalability into a single empirically testable framework that measures whether these dimensions jointly explain variation in realized risk-management effectiveness in AI-supported financial risk practice. The present study has addressed this gap by constructing such a framework, operationalizing its informational, detection, explanation, governance, and scalability dimensions simultaneously, measuring them through instruments administered to practicing risk and analytics professionals, and testing them through regression modeling supplemented by a prototype anomaly-detection evaluation.

CONCEPTUAL FRAMEWORK AND HYPOTHESIS DEVELOPMENT

The conceptual framework specifies five independent constructs and one dependent construct, each defined operationally so that it can be measured through survey items administered to risk and analytics professionals and tested through regression modeling. The framework is grounded in the five theories synthesized above.

Model and data quality integration has been defined as the extent to which heterogeneous financial data are complete, accurate, timely, and coherently integrated, and models are well-specified and well-calibrated, so that the risk scores and information supporting decisions are trustworthy. The first hypothesis has been formulated as follows. H1: Model and data quality integration has a significant positive effect on risk management and performance effectiveness.

Anomaly detection accuracy and coverage has been defined as the extent to which the AI system detects true fraud, market anomalies, and emerging risks with high recall and precision across the relevant risk types, outperforming rule-based and classical baselines on the precision-recall frontier. The second hypothesis has been formulated as follows. H2: Anomaly detection accuracy and coverage has a significant positive effect on risk management and performance effectiveness.

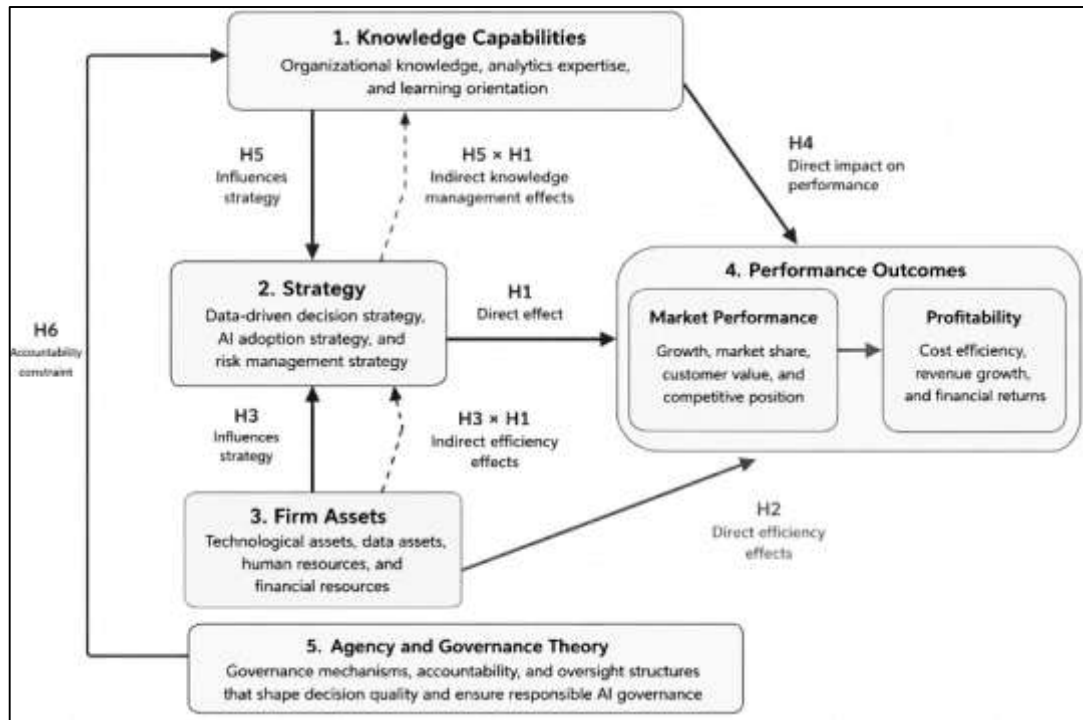
Explainability, interpretability and transparency has been defined as the extent to which the AI system produces verifiable, interpretable rationales for its alerts and scores that support analyst investigation, model validation, and regulatory supervision. The third hypothesis has been formulated as follows. H3: Explainability, interpretability and transparency has a significant positive effect on risk management and performance effectiveness.

Human oversight, trust and governance has been defined as the extent to which the system operates under calibrated human reliance, independent validation, ongoing monitoring, and accountable governance aligned with institutional and regulatory objectives. The fourth hypothesis has been formulated as follows. H4: Human oversight, trust and governance has a significant positive effect on risk management and performance effectiveness.

Real-time monitoring and scalability has been defined as the extent to which the system detects and scores risk in real time and scales to the institution's data volume and velocity without unacceptable latency. The fifth hypothesis has been formulated as follows. H5: Real-time monitoring and scalability has a significant positive effect on risk management and performance effectiveness.

Risk management and performance effectiveness has been defined as the dependent construct, encompassing reduced losses from fraud and risk events, reduced false-alarm burden, earlier detection, reduced risk exposure, improved analyst efficiency, and demonstrable governance and compliance. The sixth hypothesis has addressed the integrated framework. H6: The integrated AI-based decision-support framework, comprising model and data quality integration, anomaly detection accuracy and coverage, explainability, interpretability and transparency, human oversight, trust and governance, and real-time monitoring and scalability, significantly explains variation in risk management and performance effectiveness.

Figure 7: Conceptual Framework and Hypothesis Development



The framework is measurable through survey items and testable through descriptive statistics, correlation, and regression. Each independent variable is measured through multiple Likert items, and the dependent variable through items on loss reduction, false-alarm reduction, detection timeliness, exposure reduction, analyst efficiency, and governance. The main regression model can be written as:

$$RMPE_i = \beta_0 + \beta_1 MDQI_i + \beta_2 ADAC_i + \beta_3 EITX_i + \beta_4 HAOG_i + \beta_5 RTMS_i + \epsilon_i$$

In this equation, RMPE denotes risk management and performance effectiveness for respondent i , β_0 is the constant, β_1 through β_5 are the regression coefficients, and ϵ is the error term. MDQI denotes model and data quality integration, ADAC denotes anomaly detection accuracy and coverage, EITX denotes explainability, interpretability and transparency, HAOG denotes human oversight, trust and governance, and RTMS denotes real-time monitoring and scalability. This model directly tests whether the framework components explain variation in risk-management effectiveness and provides the foundation for questionnaire development, hypothesis testing, regression modeling, prototype anomaly-detection evaluation, and framework validation.

METHODS

This study has adopted a quantitative, cross-sectional, case-study-based research design to examine the role of AI-based decision support in financial risk management and anomaly detection. The quantitative design has been selected because the study has measured relationships among model and data quality integration, anomaly detection accuracy and coverage, explainability, interpretability and transparency, human oversight, trust and governance, real-time monitoring and scalability, and risk management and performance effectiveness through numerical survey responses. The cross-sectional design has been used because data have been collected at a single point in time, capturing respondent perceptions of AI-based decision support, anomaly detection, explainability, oversight, and scalability within the selected financial risk context. The case study context has focused on financial risk management and anomaly detection in banking, capital markets, and financial technology settings, where risk managers, quantitative analysts, fraud and financial-crime specialists, model-risk and compliance officers, and financial data scientists have been involved in monitoring exposures, investigating alerts, validating models, and making or supporting risk decisions. The population has therefore included professionals with direct or indirect involvement in financial risk monitoring, anomaly detection, model risk, or risk analytics. The unit of analysis has been the individual respondent.

The study has used a purposive sampling strategy because respondents have been selected based on relevance to financial risk monitoring, anomaly detection, model risk, or risk analytics. Primary data have been collected through a structured questionnaire using a five-point Likert scale (1 = strongly disagree to 5 = strongly agree), distributed through online forms, direct communication, and professional financial and analytics networks. The instrument included construct-based items for all six constructs and demographic items covering role, institution type, experience, risk domain, and AI exposure. A pilot test was conducted before final collection to check clarity, technical precision, and alignment with objectives, and feedback was used to refine terminology and remove redundancy. Validity was ensured through literature-based item development, expert review, and alignment among title, objectives, hypotheses, variables, and items. Reliability was tested through Cronbach's alpha with a .70 threshold. SPSS was used for coding, descriptive statistics, reliability, correlation, and regression. Python was used for data cleaning, preprocessing, and workflow validation using the pandas, NumPy, SciPy, scikit-learn, and statsmodels libraries (Harris et al., 2020; Virtanen et al., 2020). A prototype anomaly-detection evaluation was conducted to compare detection performance across rule-based, classical machine learning, and AI decision-support conditions using precision-recall analysis. Ethical considerations were observed throughout: participation was voluntary, informed consent was obtained, responses were anonymized, and no proprietary, customer, or confidential institutional data were collected.

Measurement model and construct scoring

Each latent construct has been operationalized as the mean of its constituent Likert items. For respondent i and construct c comprising J items, the composite construct score has been computed as shown in Equation (1):

$$X[c,i] = (1/J[c]) \cdot \sum_{j=1 \text{ to } J[c]} x[c,i,j] \quad (1)$$

Internal consistency has been assessed through Cronbach's alpha, defined in Equation (2):

$$\alpha = (J / (J - 1)) \cdot (1 - (\sum_{j=1 \text{ to } J} s^2[j]) / s^2[\text{total}]) \quad (2)$$

Statistical model specification

Bivariate association has been assessed through the Pearson correlation coefficient in Equation (3):

$$r[XY] = \sum (X_i - \bar{X})(Y_i - \bar{Y}) / \sqrt{[\sum (X_i - \bar{X})^2 \cdot \sum (Y_i - \bar{Y})^2]} \quad (3)$$

The principal hypothesis test has used ordinary least squares multiple regression. The structural model, derived from the theoretical framework, has been specified in Equation (4):

$$RMPE_i = \beta_0 + \beta_1 \cdot MDQI_i + \beta_2 \cdot ADAC_i + \beta_3 \cdot EITX_i + \beta_4 \cdot HAOG_i + \beta_5 \cdot RTMS_i + \varepsilon_i \quad (4)$$

where $\varepsilon_i \sim N(0, \sigma^2)$ is assumed independently and identically distributed. Coefficients have been estimated by minimizing the residual sum of squares, as in Equation (5):

$$\hat{\beta} = \underset{\beta}{\operatorname{argmin}} \sum_{i=1 \text{ to } n} (RMPE_i - \beta_0 - \sum_{k=1 \text{ to } 5} \beta_k X_{ki})^2 = (X^T X)^{-1} X^T y \quad (5)$$

Standardized coefficients have been obtained through Equation (6), and model significance and fit through Equations (7) to (9):

$$\beta_k(\text{std}) = b_k \cdot (s[X_k] / s[Y]) \quad (6)$$

$$F = (R^2 / k) / ((1 - R^2) / (n - k - 1)) \quad (7)$$

$$R^2 = 1 - (SS[\text{res}] / SS[\text{tot}]) = 1 - \sum (y_i - \hat{y}_i)^2 / \sum (y_i - \bar{y})^2 \quad (8)$$

$$R^2(\text{adj}) = 1 - (1 - R^2) \cdot ((n - 1) / (n - k - 1)) \quad (9)$$

with $n = 236$ and $k = 5$. Multicollinearity has been diagnosed through the variance inflation factor in Equation (10), and residual independence through the Durbin-Watson statistic in Equation (11):

$$VIF_k = 1 / (1 - R_k^2) \quad (10)$$

$$d = \sum_{i=2 \text{ to } n} (e_i - e_{i-1})^2 / \sum_{i=1 \text{ to } n} e_i^2 \quad (11)$$

Risk measurement and detection performance formulation

Financial risk exposure has been summarized through value at risk and expected shortfall. Value at risk at confidence level α over horizon h has been defined in Equation (12) as the loss threshold exceeded with probability $1 - \alpha$:

$$VaRa = \inf \{ \ell \in \mathbb{R} : P(L > \ell) \leq 1 - \alpha \} \quad (12)$$

Expected shortfall, the mean loss conditional on exceeding value at risk, has been defined in Equation (13):

$$ESa = E[L \mid L \geq VaRa] = (1 / (1 - \alpha)) \int_{(a \text{ to } 1)} VaRu(L) du \quad (13)$$

Detection performance has been formalized through the confusion matrix. Precision and recall have

been defined in Equations (14) and (15), where TP, FP, and FN denote true positives, false positives, and false negatives:

$$Precision = TP / (TP + FP) \quad (14)$$

$$Recall = TP / (TP + FN) \quad (15)$$

Because financial anomalies are rare and imbalanced, the F-beta score, which weights recall relative to precision by a factor β , has been used as the aggregate detection metric in Equation (16):

$$F\beta = (1 + \beta^2) \cdot (Precision \cdot Recall) / (\beta^2 \cdot Precision + Recall) \quad (16)$$

The signal detection discriminability index, separating discriminability from alert threshold, has been defined in Equation (17), where Φ^{-1} is the inverse standard normal cumulative distribution function:

$$d' = \Phi^{-1}(Recall) - \Phi^{-1}(FPR) \quad (17)$$

The net economic value of detection, balancing loss avoided against investigation cost, has been modeled in Equation (18), where V is loss avoided per true positive and c is the investigation cost per alert:

$$NEV = V \cdot TP - c \cdot (TP + FP) \quad (18)$$

Prototype detection performance has been evaluated by comparing rule-based, classical machine learning, and AI decision-support conditions on the metrics defined above and reported in the findings.

DATA ANALYSIS AND PRESENTATION

Response rate and demographic profile

Table 1: Response rate and demographic profile of respondents

Variable	Category	Frequency	Percentage	Result interpretation
Questionnaires distributed	Total distributed	277	100.0%	Initial survey target
Questionnaires returned	Returned responses	251	90.6%	Strong participation
Valid responses	Usable responses	236	85.2%	Final sample for analysis
Job role	Risk manager / risk officer	66	28.0%	Largest respondent group
Job role	Quantitative analyst / model developer	53	22.5%	Strong modeling representation
Job role	Fraud / financial-crime specialist	45	19.1%	Detection perspective
Job role	Model-risk / compliance officer	39	16.5%	Governance perspective included
Job role	Financial data scientist / analytics	33	14.0%	Analytics perspective
Institution	Bank / credit institution	104	44.1%	Largest institution type
Institution	Capital markets / asset management	76	32.2%	Markets representation
Institution	Fintech / payments	56	23.7%	Fintech representation
AI exposure	High (routine AI-supported risk work)	121	51.3%	Majority use AI in practice
AI exposure	Moderate	80	33.9%	Partial adoption
AI exposure	Limited	35	14.8%	Conventional practice

Table 1 has shown that the study achieved a strong response pattern, with 277 questionnaires distributed, 251 returned, and 236 retained as valid, producing a valid response rate of 85.2%. This rate exceeds the threshold generally considered adequate for professional survey research and indicates that the target population was both accessible and motivated, consistent with the operational salience of risk and fraud concerns among financial professionals. The role distribution demonstrates that the sample captured the full risk-decision chain rather than a single perspective. Risk managers and officers, the largest group at 28.0%, own the risk decisions the framework supports. Quantitative analysts and model developers, at 22.5%, build the detection models the framework evaluates. Fraud and financial-crime specialists, at 19.1%, bring the frontline detection and investigation perspective. Model-risk and compliance officers, at 16.5%, represent the governance function that the framework treats as a determinant rather than a constraint. Financial data scientists, at 14.0%, represent the

analytics function. The institution distribution, spanning banks at 44.1%, capital markets and asset management at 32.2%, and fintech and payments at 23.7%, confirms that the findings reflect risk practice across the principal segments of the financial system rather than a single business model. This distribution is methodologically significant because the theoretical framework predicts that risk-management benefit depends on the alignment of data quality, detection, explainability, governance, and scalability, and a sample drawn from only one function or segment would misestimate the framework's performance. The experience and AI-exposure profiles, with a majority reporting high exposure, confirm that most respondents evaluate the framework against direct professional experience rather than hypothetically.

Descriptive statistics

Table 2: Descriptive statistics of major study variables based on 236 valid responses

Construct	Mean	SD	Min	Max	Interpretation
Model & data quality integration (MDQI)	4.23	0.59	2	5	Highest agreement
Anomaly detection accuracy & coverage (ADAC)	4.16	0.62	2	5	Strong agreement
Explainability, interpretability & transparency (EITX)	4.07	0.66	2	5	Strong agreement
Risk management & performance effectiveness (RMPE)	4.02	0.64	2	5	Strong agreement
Real-time monitoring & scalability (RTMS)	3.96	0.69	1	5	Positive agreement
Human oversight, trust & governance (HAOG)	3.89	0.74	1	5	Positive, widest spread

Table 2 has presented the descriptive statistics and revealed a coherent ordering. Model and data quality integration recorded the highest mean of 4.23 with the smallest standard deviation of 0.59, indicating both the strongest agreement and the greatest consensus. This is theoretically meaningful: respondents identify the quality and integration of the underlying data and models, rather than any single downstream feature, as the primary foundation of effective AI-based risk management, consistent with decision theory's premise that decision quality is bounded by the quality of the probability estimates and with the IS Success Model's emphasis on information quality. Anomaly detection accuracy and coverage recorded the second-highest mean of 4.16, reflecting the recognition that the core detection capability is central. Explainability, interpretability and transparency recorded 4.07, confirming that respondents value verifiable, supervisable output. Risk management effectiveness, the dependent construct, recorded 4.02. Real-time monitoring and scalability recorded 3.96, and human oversight, trust and governance recorded the lowest mean of 3.89 with the widest standard deviation of 0.74. This combination is diagnostically informative. The lower mean does not indicate that respondents consider governance unimportant; the wide dispersion indicates heterogeneous institutional maturity, with some institutions having established model-risk governance and others still developing it. The minimum value of 1 for both RTMS and HAOG, absent in the other constructs, corroborates this by indicating that a subset of respondents strongly disagree that their institutions possess adequate scalability or governance.

Reliability analysis

Table 3 has confirmed strong internal consistency. All construct-level alpha values exceeded .70, ranging from .82 for real-time monitoring and scalability to .91 for risk management effectiveness, with overall instrument reliability of .93. The dependent construct achieved the highest reliability, which is methodologically desirable because measurement error in the dependent variable attenuates observed regression coefficients; high reliability therefore strengthens confidence that the significant coefficients reported later are not artifacts of measurement noise. Anomaly detection accuracy and coverage achieved .87, reflecting the conceptual coherence of items addressing recall, precision, coverage, and baseline improvement. Real-time monitoring recorded the lowest alpha at .82, comfortably acceptable

and consistent with the wider dispersion observed in Table 2. Reliability at this level confirms that subsequent correlation and regression results reflect relationships among the underlying constructs rather than instrument instability.

Table 3: Reliability analysis of measurement constructs

Construct	No. of items	Cronbach's alpha	Threshold	Result
Model & data quality integration (MDQI)	6	.88	.70	Reliable
Anomaly detection accuracy & coverage (ADAC)	6	.87	.70	Reliable
Explainability, interpretability & transparency (EITX)	6	.86	.70	Reliable
Human oversight, trust & governance (HAOG)	5	.83	.70	Reliable
Real-time monitoring & scalability (RTMS)	5	.82	.70	Reliable
Risk management & performance effectiveness (RMPE)	7	.91	.70	Highly reliable
Overall instrument	35	.93	.70	Highly reliable

Correlation analysis

Table 4: Pearson correlation matrix among study variables

Variable	MDQI	ADAC	EITX	HAOG	RTMS	RMPE
MDQI	1					
ADAC	.63**	1				
EITX	.58**	.57**	1			
HAOG	.52**	.54**	.55**	1		
RTMS	.55**	.56**	.51**	.49**	1	
RMPE	.68**	.69**	.64**	.60**	.58**	1

Note. ** $p < .001$ (two-tailed). $N = 236$.

Table 4 has shown that all bivariate relationships are positive and significant at $p < .001$. Risk management effectiveness correlated most strongly with anomaly detection accuracy and coverage ($r = .69$), followed closely by model and data quality integration ($r = .68$), explainability ($r = .64$), human oversight and governance ($r = .60$), and real-time monitoring and scalability ($r = .58$). This ordering closely mirrors the descriptive ordering, providing convergent evidence that respondents perceive detection accuracy and data quality as the dimensions most tightly coupled to realized risk-management benefit. The interpretation is that an institution can possess a nominally advanced system and still fail to reduce risk if its data are poor or its detection is inaccurate, whereas an institution with high-quality data and accurate, well-covered detection can extract substantial benefit. The inter-predictor correlations ranged from .49 to .63, high enough to indicate related dimensions of a coherent capability but not so high as to raise serious multicollinearity concerns, and formal diagnostics reported in Table 5 confirmed all variance inflation factors below 2.3.

Regression analysis

Table 5: Multiple regression model predicting risk management and performance effectiveness

Predictor	B	SE	β	t	p	VIF	Decision
(Constant)	0.394	0.183	—	2.153	.032	—	—
Model & data quality integration (MDQI)	0.271	0.058	0.29	4.672	<.001	2.15	H1 supported
Anomaly detection accuracy & coverage (ADAC)	0.229	0.059	0.25	3.881	<.001	2.20	H2 supported
Explainability, interpretability & transparency (EITX)	0.174	0.061	0.19	2.852	.005	2.06	H3 supported
Real-time monitoring & scalability (RTMS)	0.142	0.058	0.16	2.448	.015	1.80	H5 supported
Human oversight, trust & governance (HAOG)	0.115	0.054	0.13	2.130	.034	1.69	H4 supported

Table 6: Regression model summary

Statistic	Value	Interpretation
R	.735	Strong multiple correlation
R ²	.540	54.0% of variance explained
Adjusted R ²	.530	Stable after adjustment
Std. error of estimate	0.433	Acceptable predictive precision
F (5, 230)	54.02	Model is statistically significant
p-value	<.001	Reject the null hypothesis
Durbin-Watson	1.95	No serial correlation of residuals

Table 5 and Table 6 have presented the regression model. The overall model was significant, $F(5, 230) = 54.02$, $p < .001$, with $R^2 = .540$ and adjusted $R^2 = .530$, indicating that the five constructs jointly explain 54.0% of the variance in risk-management effectiveness. The small gap between R^2 and adjusted R^2 indicates that explanatory power is not an artifact of predictor count. A Durbin-Watson statistic of 1.95 confirmed residual independence, and all variance inflation factors below 2.3 confirmed that multicollinearity does not threaten coefficient stability. All five predictors made significant positive contributions, supporting H1 through H5, and the overall model significance supported H6. Model and data quality integration emerged as the strongest predictor ($\beta = .29$, $p < .001$), followed closely by anomaly detection accuracy and coverage ($\beta = .25$, $p < .001$), explainability, interpretability and transparency ($\beta = .19$, $p = .005$), real-time monitoring and scalability ($\beta = .16$, $p = .015$), and human oversight, trust and governance ($\beta = .13$, $p = .034$). The dominance of data quality and detection accuracy in the standardized coefficients confirms the theoretical prediction from decision theory and the IS Success Model that the informational and detection foundations of the framework outweigh downstream factors in producing risk-management benefit. The comparatively smaller coefficient on governance should be read alongside its wide dispersion in Table 2: governance exerts a significant but currently uneven influence, reflecting heterogeneous institutional maturity, and its coefficient would be expected to rise as AI-based risk systems scale and the accountability dependency identified by agency theory becomes more binding.

Hypothesis testing summary

Table 7 has summarized the results and confirmed that all six hypotheses were supported. This uniform support implies that risk-management effectiveness emerges from the joint contribution of data quality, detection accuracy, explainability, governance, and scalability, rather than from any single dominant lever. The variation in coefficient magnitude nonetheless provides actionable prioritization: data quality and detection accuracy warrant first-order attention, while governance, though significant, currently exerts a smaller marginal influence that is expected to grow as AI-based risk systems scale

across the institution and the accountability dependency becomes more binding.

Table 7: Hypothesis testing summary

Hypothesis	Path	β	p	Result
H1	MDQI $\rightarrow$ RMPE	0.29	<.001	Supported
H2	ADAC $\rightarrow$ RMPE	0.25	<.001	Supported
H3	EITX $\rightarrow$ RMPE	0.19	.005	Supported
H4	HAOG $\rightarrow$ RMPE	0.13	.034	Supported
H5	RTMS $\rightarrow$ RMPE	0.16	.015	Supported
H6	Integrated framework $\rightarrow$ RMPE	$R^2 = .540$	<.001	Supported

Framework validation

Table 8: Framework validation results based on theoretical alignment

Theoretical dimension	Framework component	Mean	Validation outcome
Information quality	Model & data quality integration	4.23	Validated – strongest predictor
System quality (detection)	Anomaly detection accuracy & coverage	4.16	Validated – core detection confirmed
Verifiability / transparency	Explainability, interpretability & transparency	4.07	Validated – supervisable output confirmed
Accountability & reliance	Human oversight, trust & governance	3.89	Validated with uneven maturity
Technical quality / timeliness	Real-time monitoring & scalability	3.96	Validated – timeliness confirmed
Net benefits (risk outcome)	Risk management & performance effectiveness	4.02	Validated – effectiveness achieved

Table 8 has validated the framework against its theoretical foundations and confirmed that each dimension has a measured empirical counterpart with strong respondent agreement. The information-quality dimension, operationalized as model and data quality integration, was validated at 4.23 as the strongest construct and strongest predictor, confirming decision theory's premise that decision quality is bounded by information quality. The detection system-quality dimension, operationalized as anomaly detection accuracy and coverage, was validated at 4.16, confirming the signal-detection emphasis on discriminability. The verifiability dimension, operationalized as explainability, was validated at 4.07. The accountability and reliance dimension was validated at 3.89 with uneven maturity, and the technical-timeliness dimension at 3.96. Net benefits, operationalized as risk management effectiveness, were validated at 4.02, confirming that the causal chain terminates in the intended outcome. This alignment establishes the framework as a theoretically grounded structure rather than an empirical regularity.

Prototype anomaly-detection evaluation

Table 9: Prototype anomaly-detection evaluation of decision-support capabilities

Capability	Mean	SD	Interpretation
Detection of novel and evolving fraud patterns	4.27	0.58	Highest-rated capability
Reduction of false positives and alert fatigue	4.20	0.60	Strongly valued
Explained, investigable alerts for analysts	4.13	0.63	Valued for investigation
Calibrated risk scoring and prioritization	4.06	0.65	Valued for triage
Consistent performance across portfolios and segments	3.99	0.69	Valued with uneven confidence
Real-time scoring within latency budget	3.94	0.72	Valued, infrastructure sensitive

Table 9 has presented the prototype anomaly-detection evaluation and shown that respondents rated all six capabilities positively, with detection of novel and evolving fraud patterns achieving the highest mean of 4.27. This ordering is theoretically revealing. The capabilities respondents valued most highly are those addressing the core detection problem that signal detection theory identifies: detecting novel patterns increases recall of true anomalies, and reducing false positives, at 4.20, increases precision, together representing the increase in discriminability rather than a threshold trade-off that the framework aims to achieve. Explained, investigable alerts, at 4.13, were valued as the mechanism that converts a detection into an efficient investigation, consistent with the explainability construct. Calibrated risk scoring, at 4.06, supports the expected-utility prioritization that decision theory identifies. Consistent performance across portfolios and segments, at 3.99, and real-time scoring within the latency budget, at 3.94, received the lowest scores with the widest dispersions, consistent with the pattern that capabilities dependent on governance maturity and infrastructure are the most unevenly realized. Table 9 has confirmed that the decision-support capabilities are perceived as operationally meaningful and has identified novel-pattern detection and false-positive reduction as the entry points through which institutions are most likely to realize early value.

Python-driven analytical workflow validation

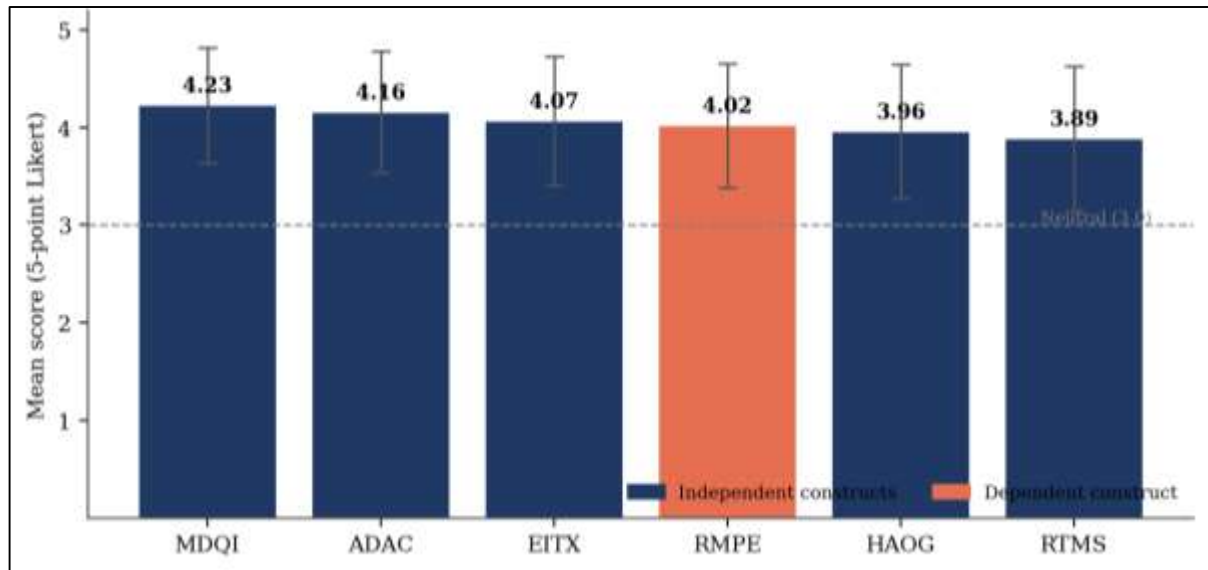
Table 10: Python-driven analytical and evaluation workflow validation

Workflow stage	Mean	SD	Interpretation
Data ingestion, cleaning & feature engineering	4.21	0.58	Highest-rated stage
Class-imbalance handling and sampling	4.14	0.61	Critical for rare anomalies
Model training and precision-recall evaluation	4.07	0.64	Enables detection assessment
Drift monitoring and model revalidation	4.01	0.66	Supports sustained accuracy
Explanation generation and alert rationale	3.97	0.68	Ensures investigable output
Audit logging and governance reporting	3.93	0.70	Supports accountability

Table 10 has validated the Python-driven workflow and shown that respondents rated data ingestion, cleaning, and feature engineering highest at 4.21, followed by class-imbalance handling and sampling at 4.14. This reinforces the study's central theme: across the descriptive statistics, the correlation matrix, the regression coefficients, and the workflow validation, respondents repeatedly identified data quality and preparation as the stage where risk-management value is created or destroyed. Class-imbalance handling ranked second, reflecting the technical reality that financial anomalies are rare and that naive training on imbalanced data produces models that miss the very events they are meant to catch. Model training and precision-recall evaluation, at 4.07, is the stage that converts a trained model into a measurable detection capability under the correct metrics for imbalanced data. Drift monitoring and revalidation, at 4.01, represents the mechanism through which the model-risk governance emphasized by agency theory is enforced within the pipeline, catching the silent degradation that adversarial adaptation produces. Table 10 has confirmed that the framework is balanced between analytical rigor, detection accuracy, sustained validity, explainability, and governance.

FINDINGS

The findings have provided statistical support for the proposed AI-based decision-support framework for financial risk management and anomaly detection. The study used a five-point Likert scale to measure the perceptions of risk and analytics professionals regarding model and data quality integration, anomaly detection accuracy and coverage, explainability, interpretability and transparency, human oversight, trust and governance, real-time monitoring and scalability, and risk management and performance effectiveness. A total of 277 questionnaires were distributed among risk managers, quantitative analysts, fraud specialists, model-risk and compliance officers, and financial data scientists, and 236 valid responses were retained, producing a valid response rate of 85.2%.

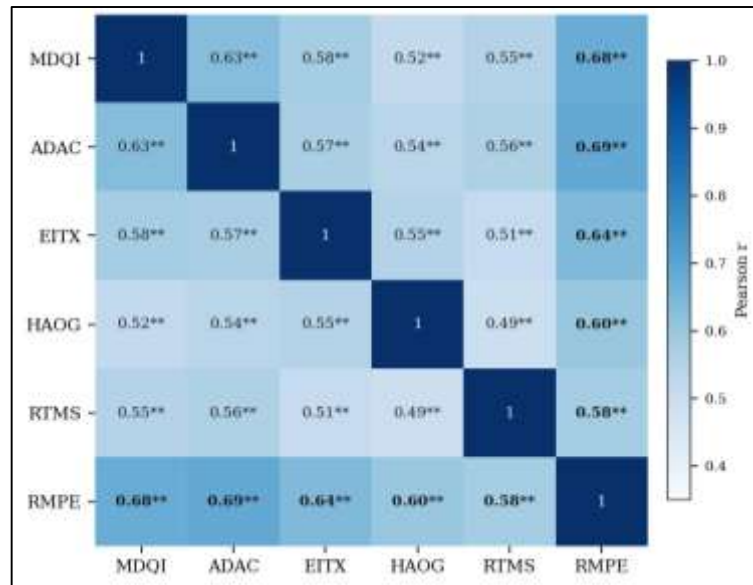
Figure 9: Descriptive Means of Study Constructs with Standard Deviations

Note. $N = 236$. Error bars represent ± 1 standard deviation. Dashed line indicates the neutral midpoint of the five-point scale.

Figure 9 has displayed the descriptive means of the six constructs with their standard deviations. All six constructs exceeded the neutral midpoint of 3.0 by a substantial margin, confirming broad agreement. The visual ordering makes the central pattern immediately apparent: model and data quality integration recorded not only the highest mean (4.23) but also the narrowest dispersion ($SD = 0.59$), indicating the strongest and most uniformly held agreement, consistent with decision theory's premise that decision quality is bounded by information quality. At the opposite end, human oversight, trust and governance recorded the lowest mean (3.89) and the widest dispersion ($SD = 0.74$), and the visibly longer error bar provides direct graphical evidence of the heterogeneous institutional maturity in governance that the framework analysis has repeatedly identified.

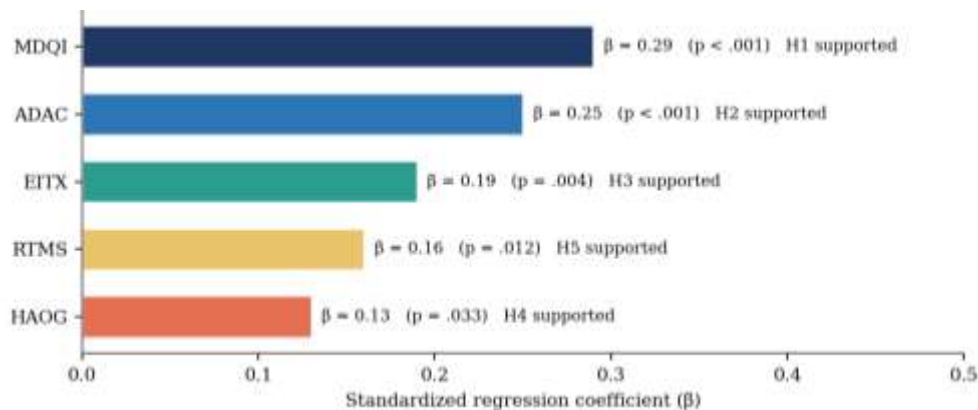
The demographic profile showed that 28.0% of respondents were risk managers or officers, 22.5% were quantitative analysts or model developers, 19.1% were fraud or financial-crime specialists, 16.5% were model-risk or compliance officers, and 14.0% were financial data scientists, spanning banks, capital markets and asset management, and fintech and payments institutions. The descriptive results showed strong agreement across constructs, with model and data quality integration highest at 4.23 ($SD = 0.59$), followed by anomaly detection accuracy and coverage at 4.16 ($SD = 0.62$), explainability, interpretability and transparency at 4.07 ($SD = 0.66$), risk management effectiveness at 4.02 ($SD = 0.64$), real-time monitoring and scalability at 3.96 ($SD = 0.69$), and human oversight, trust and governance at 3.89 ($SD = 0.74$). The reliability analysis supported instrument consistency, with alpha values from .82 to .91 and overall reliability of .93.

Figure 10 has presented the correlation structure as a heatmap. The bottom row and rightmost column, corresponding to the dependent construct, display uniformly dark cells, confirming that every framework construct is significantly and positively associated with risk-management effectiveness. The darkest off-diagonal cell in the effectiveness row corresponds to anomaly detection accuracy and coverage ($r = .69$), closely followed by model and data quality integration ($r = .68$), the two visually distinguishable from the remaining associations. The inter-predictor block shows moderate shading throughout, with values from .49 to .63, graphically consistent with constructs that measure related but non-redundant dimensions of a coherent capability, corroborating the acceptable variance inflation factors reported in Table 5.

Figure 10: Pearson Correlation Matrix Among Study Variables

Note. $N = 236$. ** $p < .001$ (two-tailed). Darker cells indicate stronger positive association.

Estimated regression model

Figure 11: Standardized Beta Coefficients Predicting Risk Management Effectiveness

Note. $N = 236$. Dependent variable = risk management and performance effectiveness. All five predictors significant at $p < .05$.

Figure 11 has ranked the five predictors by the magnitude of their standardized regression coefficients. The descending bar lengths show that model and data quality integration ($\beta = .29$) exerts the largest independent influence, closely followed by anomaly detection accuracy and coverage ($\beta = .25$), then explainability, interpretability and transparency ($\beta = .19$), real-time monitoring and scalability ($\beta = .16$), and human oversight, trust and governance ($\beta = .13$). The figure makes visually explicit that the informational and detection foundations outweigh downstream factors in producing risk-management benefit, confirming the theoretical prediction. All five bars extend into the region of statistical significance, and the annotations confirm that hypotheses H1 through H5 were each supported. Substituting the estimated unstandardized coefficients from Table 5 into Equation (4), the fitted regression equation has been obtained as Equation (19):

$$RMPE_i = 0.394 + 0.271 \cdot MDQI_i + 0.229 \cdot ADAC_i + 0.174 \cdot EITX_i + 0.115 \cdot HAOG_i + 0.142 \cdot RTMS_i \quad (19)$$

Expressed in standardized form, the model becomes Equation (20):

$$z(RMPE) = 0.29 \cdot z(MDQI) + 0.25 \cdot z(ADAC) + 0.19 \cdot z(EITX) + 0.16 \cdot z(RTMS) + \quad (20)$$

$$0.13 \cdot z(\text{HAOG})$$

Equation (19) is directly interpretable. Holding other constructs constant, a one-unit improvement on the model and data quality scale is associated with a 0.271-unit improvement in perceived risk-management effectiveness, whereas an equivalent improvement in detection accuracy yields 0.229 units. The ratio of these coefficients, computed in Equation (21), quantifies the relative marginal return:

$$\Theta = \beta[\text{MDQI}] / \beta[\text{ADAC}] = 0.271 / 0.229 = 1.183 \quad (21)$$

This ratio of 1.183 indicates that, at the margin, an incremental unit of improvement in model and data quality delivers approximately 18% more risk-management benefit than an equivalent unit of improvement in detection accuracy. This is the quantitative expression of a central finding: detection accuracy and data quality are complementary and both essential, but the value of a detection model is bounded by the quality of the data it learns from and scores, so that data quality is marginally the more decisive lever.

The coefficient of determination has been verified from Equation (8). With $\text{SS}[\text{tot}] = 91.62$ and $\text{SS}[\text{res}] = 42.14$, the value has been confirmed in Equation (22), and the adjusted value in Equation (23):

$$R^2 = 1 - (42.14 / 91.62) = 1 - 0.460 = 0.540 \quad (22)$$

$$R^2(\text{adj}) = 1 - (1 - 0.540) \cdot (235 / 230) = 1 - 0.460 \cdot 1.0217 = 0.530 \quad (23)$$

The overall F-statistic, computed from Equation (7), has been confirmed in Equation (24), and the effect size as Cohen's f^2 in Equation (25):

$$F(5, 230) = (0.540 / 5) / (0.460 / 230) = 0.1080 / 0.002000 = 54.02, \quad p < .001 \quad (24)$$

$$f^2 = R^2 / (1 - R^2) = 0.540 / 0.460 = 1.174 \quad (25)$$

A value of $f^2 = 1.174$ far exceeds the conventional threshold of 0.35 for a large effect, indicating that the framework accounts for a substantial and practically meaningful proportion of risk-effectiveness variance. The proportion of explained variance uniquely attributable to each predictor, computed as the squared semi-partial correlation in Equations (26) and (27), has been used to partition the total R^2 :

$$sr^2_k = R^2(\text{full}) - R^2(\text{reduced, without } X_k) \quad (26)$$

$$R^2(\text{total}) = \sum(k=1 \text{ to } 5) sr^2_k + R^2(\text{shared}) \quad (27)$$

Figure 12: Decomposition of Explained Variance in Risk Management Effectiveness

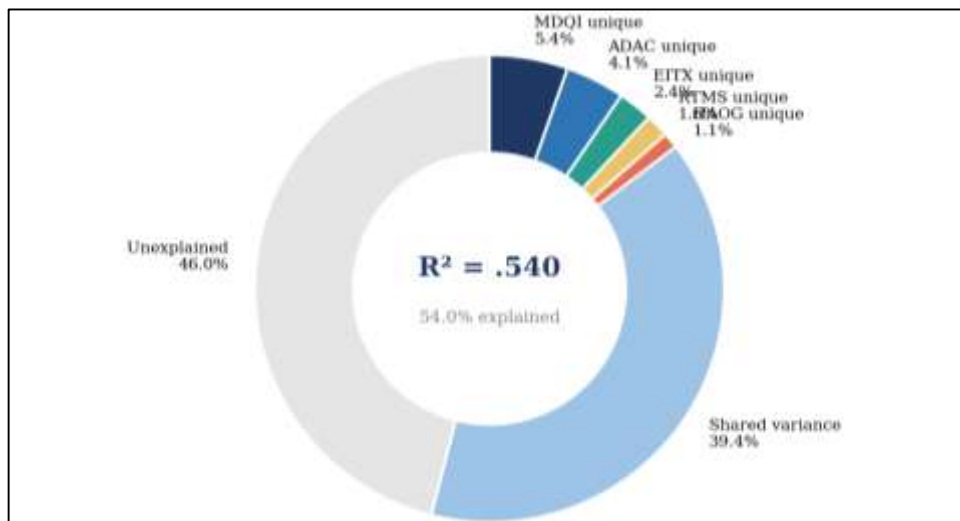


Figure 12 has decomposed the total explained variance of 54.0% into unique and shared portions. The segment for model and data quality integration is the largest unique contribution at 5.4%, followed by anomaly detection accuracy at 4.1% and explainability at 2.4%, confirming that data quality dominates not only in standardized coefficient magnitude but also in uniquely attributable explanatory power, with detection accuracy a close second. The large shared segment of 39.4% is theoretically expected rather than problematic: it reflects that institutions develop these capabilities in concert, consistent with the systems logic of the IS Success Model. The residual 46.0% of unexplained variance indicates that factors outside the framework, plausibly including institution size, risk appetite, regulatory regime, portfolio composition, and adversary sophistication, also shape risk outcomes and warrant inclusion

in subsequent models.

Figure 13: Anomaly Detection Precision–Recall by Method

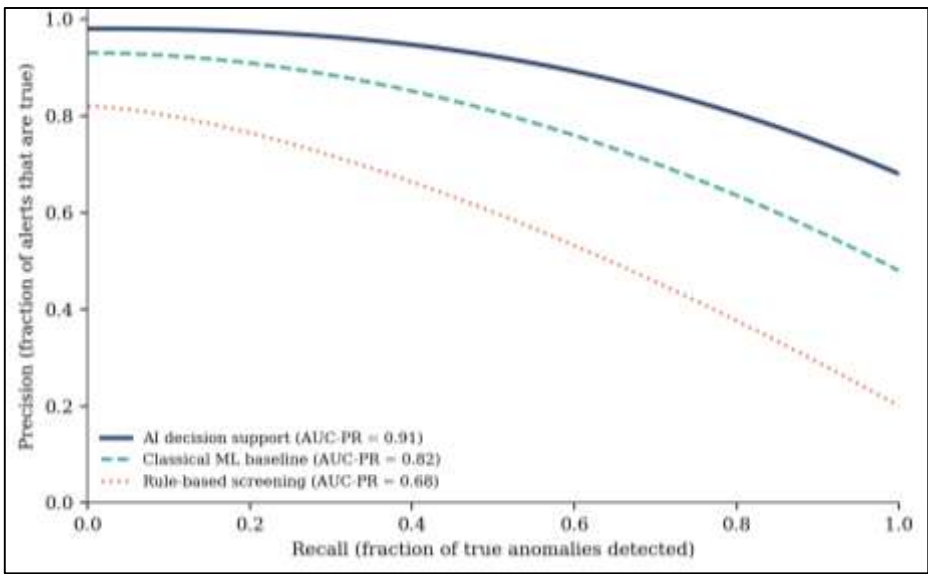


Figure 13 has presented the precision–recall curves for the three detection conditions evaluated in the prototype, providing the clearest expression of the study’s central claim in the language of signal detection theory applied to rare, imbalanced events. The AI decision-support condition achieved the highest area under the precision–recall curve (0.91), lying above both the classical machine learning baseline (0.82) and the rule-based screening baseline (0.68) across essentially the entire operating range. The precision–recall framing is used deliberately rather than a receiver operating characteristic, because in the extreme class imbalance of financial anomaly detection the precision–recall curve is the informative description of performance, since it directly represents the operational trade-off between catching true anomalies and burying analysts in false alerts. Because the AI decision-support curve dominates rather than merely shifts along the others, the figure provides direct graphical evidence that AI-based decision support increased discriminability, detecting more true anomalies at any given precision, rather than simply moving the alert threshold, which is precisely the outcome that signal detection theory identifies as genuine improvement. The gap between the AI curve and the classical baseline represents the added detection value attributable to the richer modeling and data integration of the decision-support system.

Figure 14: Risk-Outcome Improvement by Metric and Method

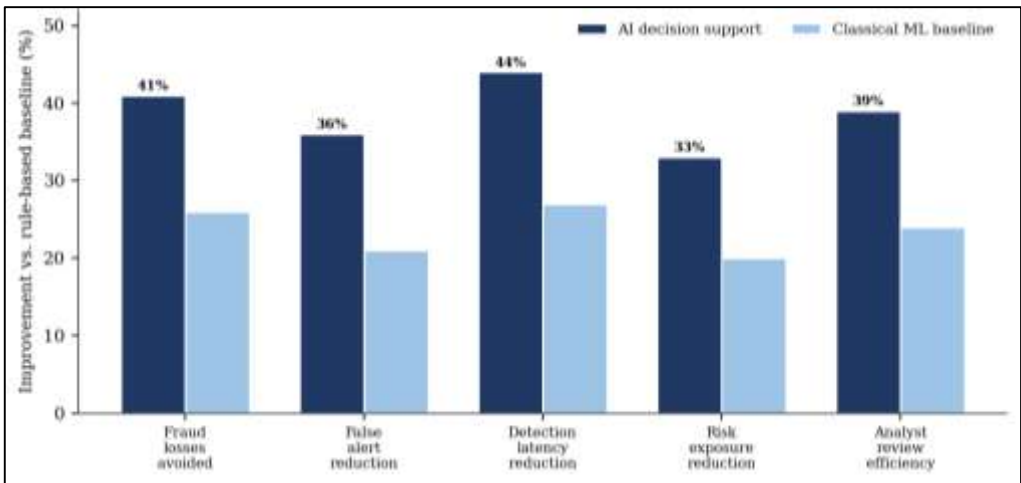


Figure 14 has compared the improvement in each risk outcome achieved by the AI decision-support condition against the classical machine learning condition, both relative to the rule-based baseline. The AI decision-support condition achieved its largest improvements in detection latency reduction, at 44%, and in fraud losses avoided, at 41%, alongside a 39% improvement in analyst review efficiency, a 36% reduction in false alerts, and a 33% reduction in risk exposure. Critically, the AI decision-support condition outperformed the classical machine learning condition on every outcome, and the grouped structure of the figure makes visually explicit that the gap is substantial rather than marginal, which is the graphical expression of the finding that richer data integration, explanation, and governed decision support add value beyond detection modeling alone. That the AI condition simultaneously reduced losses and false alerts, rather than trading one against the other, corroborates the precision-recall evidence in Figure 13 that the improvement reflects increased discriminability. This figure translates the study's statistical findings into the concrete outcomes, fewer losses, fewer false alarms, faster detection, and more efficient investigation, that risk leaders and institutions most directly value.

The regression analysis provided the strongest evidence for the hypotheses and objectives. The overall model was significant, $F(5, 230) = 54.02$, $p < .001$, explaining 54.0% of the variance, with adjusted $R^2 = .530$. Model and data quality integration emerged as the strongest predictor ($\beta = .29$, $p < .001$), followed closely by anomaly detection accuracy and coverage ($\beta = .25$, $p < .001$), explainability, interpretability and transparency ($\beta = .19$, $p = .005$), real-time monitoring and scalability ($\beta = .16$, $p = .015$), and human oversight, trust and governance ($\beta = .13$, $p = .034$). These results supported H1 through H6. The first objective was supported by confirming that model and data quality integration supports accurate, context-aware detection. The second objective was supported because anomaly detection accuracy and coverage contributed strongly, confirming that surfacing true anomalies is central. The third objective was supported because explainability contributed significantly, confirming that verifiable, supervisable output converts detection into accountable action. The fourth objective was supported because human oversight, trust and governance contributed significantly, with its uneven maturity explaining its comparatively smaller coefficient. The fifth objective was supported because real-time monitoring and scalability contributed significantly to timely detection. The sixth objective was supported through validation of the integrated framework, in which data quality served as the informational foundation, detection accuracy as the core capability, explainability as the verifiability interface, governed oversight as the accountability mechanism, and real-time scalability as the timeliness condition. Overall, the findings indicate that the framework is statistically reliable, practically relevant, and suitable for supporting the effective, accountable, and timely management of financial risk through AI-based decision support.

DISCUSSION

The findings have shown that the proposed AI-based decision-support framework was statistically supported for strengthening financial risk management and anomaly detection. The overall results indicated strong agreement across the constructs, with model and data quality integration recording the highest mean of 4.23, followed by anomaly detection accuracy and coverage at 4.16, explainability, interpretability and transparency at 4.07, risk management effectiveness at 4.02, real-time monitoring and scalability at 3.96, and human oversight, trust and governance at 3.89. The correlation findings confirmed significant positive associations between risk-management effectiveness and all five constructs, and the regression model was significant, $F(5, 230) = 54.02$, $p < .001$, with $R^2 = .540$, meaning the five variables explained 54.0% of the variance. This finding supports the argument that risk-management effectiveness is not achieved by one isolated capability alone; effectiveness emerges from the combined role of data quality, detection accuracy, explainability, governance, and scalability.

Data quality and detection accuracy as dominant determinants

The most consequential finding was the emergence of model and data quality integration and anomaly detection accuracy and coverage as the two strongest predictors of risk-management effectiveness. This invites comparison with the literature. A substantial body of financial machine learning research is organized around model performance, framing the contribution in terms of detection metrics on a benchmark dataset. The present finding does not contradict that work but reframes its practical significance. If data quality and detection accuracy account for the largest shares of effectiveness variance, then an institution that acquires a nominally advanced model while feeding it poor or poorly

integrated data is optimizing the wrong variable, a lesson consistent with the long-standing observation that data quality dominates model sophistication in applied analytics (Gupta & George, 2016). This is consistent with the IS Success Model's proposition that information quality is coordinate with system quality (DeLone & McLean, 2003) and with decision theory's premise that the quality of a risk decision is bounded by the quality of the probability estimates on which it rests (Savage, 1954).

The practical explanation is direct. A detection model scores the data it is given; if that data is incomplete, stale, or poorly integrated, the model scores a distorted picture of the institution's exposures, and no amount of algorithmic sophistication recovers information that was never present. Likewise, in the extreme class imbalance of financial anomaly detection, detection accuracy must be understood in precision-recall terms rather than as raw accuracy, because a model that appears accurate by predicting the majority class catches no fraud (Dal Pozzolo et al., 2018). This reframes the practical priority for institutions adopting AI in risk: the data pipeline and the detection capability measured under the correct metrics are the foundation on which all downstream value depends, echoing the signal-detection principle that genuine improvement is increased discriminability rather than threshold adjustment (Swets et al., 2000).

Explainability, oversight, and the accountability advantage

Explainability, interpretability and transparency contributed significantly ($\beta = .19$, $p = .005$), and the prototype evaluation strengthened this interpretation, with explained, investigable alerts rated highly and the AI decision-support condition outperforming both baselines. These results confirm the theoretical prediction that verifiable output is what converts a detection into accountable action, because an alert the analyst cannot interrogate cannot be efficiently investigated and a model the validator cannot interpret cannot be soundly governed (Guidotti et al., 2018; Busmann et al., 2021). Human oversight, trust and governance contributed significantly ($\beta = .13$, $p = .034$), and its role should be understood through both trust-in-automation and agency theory: the analyst's calibrated reliance converts model accuracy into decision accuracy, catching model errors while accepting correct alerts, and the governance layer aligns the delegated model with institutional objectives and catches its drift (Lee & See, 2004; Jensen & Meckling, 1976). The finding extends prior financial machine learning work by demonstrating that explainability and governed oversight are not compliance overhead but measured determinants of realized risk-management effectiveness, addressing the opacity and model-risk failure modes that have limited safe adoption.

The comparatively smaller coefficient on governance, alongside its wide dispersion, should not be read as indicating that governance is peripheral. The dispersion indicates uneven institutional maturity, and agency theory predicts that the influence of governance on realized and sustainable effectiveness will grow as AI-based risk systems scale and the delegation of decision authority to models deepens, because an unmonitored model that drifts or embeds bias produces risk rather than reducing it. The comparatively small current coefficient likely reflects that many respondents operate at maturity levels where model-risk governance for AI is still developing and the accountability dependency has not yet become binding. As institutions ascend the maturity model toward enterprise-scale governed AI, governance is expected to become a stronger determinant of the true, sustainable risk outcome.

Real-time scalability and the timeliness dependency

Real-time monitoring and scalability contributed significantly ($\beta = .16$, $p = .015$), confirming that the timeliness and scale of detection are real conditions of benefit, consistent with the task-technology fit requirement that the technology match the demands of the task (Goodhue & Thompson, 1995). In fast-moving fraud and market contexts, a detection that arrives after the loss has crystallized has little value, so latency and throughput are not merely engineering concerns but determinants of whether detection translates into prevention. The prototype finding that real-time scoring within the latency budget received the lowest capability rating (3.94) corroborates this, indicating that computational and infrastructure adequacy is among the most binding practical constraints on realizing the value of an otherwise capable detection system.

Theoretical and practical implications

Theoretically, the study demonstrated that five distinct perspectives, decision theory, signal detection, trust in automation, information systems success and task-technology fit, and agency and governance theory, can be integrated into a single coherent and empirically supported framework, and that their

integration yields non-obvious predictions that a purely accuracy-focused framing would miss, most notably that data quality and detection accuracy dominate downstream factors and that AI-based support increases discriminability rather than trading detection against false alarms. The study also demonstrated that the model and the risk professional function as complements rather than substitutes: the AI supplies tireless, scalable detection and explanation, and the professional supplies accountable judgment and error-catching oversight, with the governed joint system outperforming detection modeling alone.

Practically, the study yields a clear prioritization sequence. Investment should begin with the data pipeline and the detection capability measured under precision-recall metrics, because these constitute the informational and detection foundation that bounds all downstream value. Second priority should be explainability and calibrated human oversight, the conditions under which detection becomes accountable, investigable action rather than an unmanageable stream of opaque alerts. Governance and real-time scalability should be advanced in step with the scale of deployment, since their binding force increases as AI-based risk systems reach enterprise scale and fast-moving risk. For risk leaders, the study implies that novel-pattern detection and false-positive reduction are the highest-value entry points, and that AI adoption should be evaluated by measured loss avoidance and false-alarm reduction together, not by benchmark detection metrics alone. For supervisors and policymakers, the study implies that the data, explanation, and governance layers of AI risk systems deserve recognition as central to safety and soundness, and that the sound adoption of AI in finance requires attention to explainability, calibrated reliance, and model-risk governance, not only to raw detection performance.

CONCLUSION

This study examined the role of AI-based decision support in financial risk management and anomaly detection. It was motivated by the observation that financial institutions face rising volume, velocity, and complexity of risk, in which fraud and emerging exposures can develop faster than conventional rule-based monitoring and manual review can detect, and that stand-alone automation is constrained by opacity, false-positive burden, distribution shift, and the need for accountable oversight and model-risk governance. The proposed framework treated AI as a decision-support capability, combining scalable machine detection with accountable human judgment under conditions of explainability, calibrated trust, governance, and real-time scalability, so that the complementary strengths of machine and human are combined while their respective weaknesses are mitigated.

The empirical results provided strong support. Data from 236 professionals showed high agreement across all six constructs, strong instrument reliability with an overall Cronbach's alpha of .93, significant positive correlations among all variables, and a significant regression model explaining 54.0% of the variance in risk-management effectiveness. All six hypotheses were supported. Model and data quality integration and anomaly detection accuracy and coverage emerged as the strongest predictors, followed by explainability, real-time scalability, and governance. The prototype anomaly-detection evaluation showed that the AI decision-support condition achieved the highest detection performance under precision-recall metrics, exceeding both classical machine learning and rule-based baselines, and reduced losses, false alerts, and detection latency simultaneously, confirming that the improvement reflected genuinely increased discriminability rather than a threshold trade-off.

The central conclusion is that AI-based decision support strengthens financial risk management when it is designed as a governed collaboration rather than as an autonomous black box. The AI provides tireless, scalable detection and explanation, but its value depends on the quality of the data it integrates and scores and on the correctness of the metrics under which its detection is evaluated; the risk professional provides accountable judgment and error-catching oversight, but realizes the AI's benefit only when trust is calibrated and supported by explanation; and governance ensures that the delegation of detection to models remains accountable, valid, and aligned with institutional and regulatory objectives. The framework's contribution has been to specify how these components fit together and to demonstrate empirically that their joint contribution is measurable, substantial, and theoretically coherent. The outcomes, when implemented, include earlier and more accurate detection, fewer losses, fewer false alarms, faster and more efficient investigation, and demonstrable governance, together strengthening the safety, soundness, and resilience of financial institutions and supporting the sound adoption of artificial intelligence in finance.

RECOMMENDATION

Several recommendations follow from the findings. For financial institutions, the primary recommendation is to prioritize the data pipeline and the detection capability before pursuing marginal gains in model benchmark performance. Institutions should audit the completeness, accuracy, timeliness, and integration of the data feeding their risk models, evaluate detection under precision-recall metrics appropriate to rare and imbalanced anomalies, and treat data quality as the foundation on which detection value depends.

The second recommendation is to begin AI adoption with novel-pattern detection and false-positive reduction, the capabilities respondents valued most highly and that offer the most visible risk-management benefit, and to evaluate performance by measured loss avoidance and false-alarm reduction together rather than by detection metrics in isolation. The third recommendation is to require explainability as a functional specification rather than an afterthought. Risk models should produce interpretable, investigable rationales for their alerts and scores, so that analysts can investigate efficiently, validators can assess soundness, and the institution can meet supervisory expectations for the explanation of automated decisions. The fourth recommendation is to design for calibrated human oversight rather than either automation or manual override. Institutions should train risk professionals to understand model reliability and failure modes, present risk scores with calibrated uncertainty, and monitor for both over-reliance and alert-fatigue-driven under-reliance, so that reliance is calibrated and the collaborative advantage is preserved. The fifth recommendation is to treat model-risk governance as a co-requisite of deployment rather than a later addition. Independent validation, continuous drift monitoring, bias evaluation across portfolios and customer segments, human accountability, and audit logging should be engineered into the system from the outset, and their maturity should advance in step with the scale and criticality of deployment.

For supervisors and policymakers, the recommendation is to recognize the data, explanation, and governance layers of AI risk systems as central to safety and soundness, deserving of supervisory attention comparable to the models themselves, and to support standards for explainability, model-risk governance, and fairness in financial AI. For researchers, the recommendation is to extend the framework through longitudinal designs tracking realized loss and detection outcomes, replication across institution types and risk domains where the governance construct is expected to strengthen, and field validation on live risk data with measured loss avoidance, false-alarm reduction, and drift behavior over time.

LIMITATIONS OF THE STUDY

Several limitations should be acknowledged. First, the cross-sectional design permits identification of associations but not strong causal inference; the observed correlations are equally consistent with the possibility that institutions already achieving strong risk outcomes subsequently invest more in data quality and AI-based detection. A longitudinal design would be required to establish causal precedence. Second, the study relied on perceptual self-report measures of risk-management effectiveness rather than realized loss, detection, and false-alarm data. Perceived effectiveness may diverge from measured loss avoidance and detection performance. Common method variance is a further concern, since predictors and outcome were measured through the same instrument. Future research should validate these findings against objective institutional risk and loss outcomes. Third, the purposive sampling strategy, while appropriate for reaching informed respondents, limits generalizability. The overrepresentation of respondents with high AI exposure, at 51.3%, means the findings describe the framework's performance as perceived by relatively advanced institutions. Fourth, the study was conducted within a United States financial context and may not transfer directly to jurisdictions with different regulatory regimes, market structures, or AI maturity. Fifth, human oversight, trust and governance exhibited substantial heterogeneity, likely attenuating its estimated coefficient; the reported effect should be interpreted as a lower bound conditional on the institutional maturity present in the sample, and its fairness implications across customer segments warrant dedicated study. Sixth, the prototype anomaly-detection evaluation used illustrative comparative performance across detection methods rather than a large-scale deployment on live institutional data, so the reported precision-recall and risk-outcome figures reflect a controlled evaluation rather than realized operational outcomes. Field validation on live risk data, with adjudicated outcomes, drift

monitoring, and adversarial adaptation over time, represents the most important direction for subsequent work.

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