Decision Intelligence Framework Integrating Big Data Analytics for Enterprise Financial Risk Management under Saudi Vision 2030.

Abstract:

Enterprise financial risk management is being reshaped by the convergence of high-volume data, machine learning, explainable analytics, and digital decision support. Yet many organizations still separate data engineering, predictive modelling, risk governance, and managerial judgment, creating a gap between analytical insight and accountable action. This review develops a Decision Intelligence Framework integrating Big Data Analytics for enterprise financial risk management in the context of Saudi Vision 2030. Using a structured integrative review, the study synthesizes peer-reviewed evidence on big data analytics capabilities, enterprise risk management, credit and fraud analytics, explainable artificial intelligence, banking digitalization, and Saudi financial-sector transformation. The synthesis identifies five recurring requirements: trusted multi-source data, risk-oriented analytical capability, explainability and model governance, decision orchestration with human accountability, and continuous learning from outcomes. The proposed framework links these requirements through a closed-loop architecture that converts internal and external data into risk signals, scenarios, recommended actions, approvals, controls, and feedback. The review argues that predictive accuracy alone is insufficient for enterprise financial risk management because risk decisions must also be timely, interpretable, auditable, and aligned with risk appetite. In Saudi enterprises, the framework is particularly relevant to expanding digital finance, open banking, cybersecurity exposure, investment diversification, and the broader objective of a resilient and technologically advanced financial sector. The paper contributes by connecting fragmented analytics and risk literatures into an integrated decision architecture and by specifying research priorities for validation in large Saudi corporations. Practical implications emphasize data governance, model-risk controls, cross-functional ownership, and staged implementation rather than technology-first adoption.

Keywords: Decision intelligence; big data analytics; enterprise risk management; financial risk; explainable AI; Saudi Vision 2030

1. Introduction

Large enterprises increasingly manage financial risk in environments characterized by volatile markets, dense digital transactions, interconnected supply chains, cyber threats, regulatory change, and rapidly expanding data volumes. Traditional enterprise risk management (ERM) provides useful governance structures for identifying, assessing, and treating risk, but many implementations remain periodic, siloed, and dependent on backward-looking indicators. By contrast, Big Data Analytics (BDA) can integrate heterogeneous information and generate predictive or prescriptive signals at greater speed. The strategic problem is therefore not simply whether firms possess more data or more sophisticated models, but whether analytics are embedded in a disciplined process that converts evidence into accountable decisions.

Research on BDA capabilities shows that business value depends on combinations of infrastructure, management capability, analytical skills, organizational routines, and the ability to translate data into action. Yasmin et al. (2020) identify infrastructure and managerial capabilities as central elements of analytics-enabled performance, while Mikalef et al. (2020) show that analytics capability affects competitive performance through dynamic and operational capabilities. Upadhyay and Kumar (2020) similarly demonstrate that organizational culture and internal analytical knowledge shape the value created by BDA. In emerging-market firms, Shamim et al. (2020) connect BDA capability to decision-making performance, and Awan et al. (2021) emphasize the mediating role of data-driven insight in decision quality. More recent synthesis by Huynh et al. (2023) nevertheless finds conceptual fragmentation in the BDA-capability literature, indicating that possessing analytics resources does not automatically produce reliable decisions.

The financial-risk literature reveals a parallel problem. Machine learning has improved default prediction, anomaly detection, and fraud screening, but it can create opacity, model risk, data drift, and governance challenges. Shi et al. (2022) show the growing breadth of machine-learning methods in credit risk, whereas Bussmann et al. (2021), Dastile and Celik (2021), and de Lange et al. (2022) demonstrate why explainability is necessary when complex models influence lending and risk decisions. Financial fraud research likewise shows strong potential for machine learning, while warning that class imbalance, changing adversarial behavior, data quality, and deployment constraints complicate real-world use (Hilal et al., 2022; Ali et al., 2022; Ashtiani and Raahemi, 2022). These studies imply that analytical sophistication must be joined to governance and decision controls.

This integration is especially relevant in Saudi Arabia. Vision 2030 has positioned digital transformation, financial-sector development, private-sector growth, innovation, and economic diversification as interconnected national priorities. Empirical Saudi research reports expanding adoption of BDA, fintech, AI, digital banking, open banking, and cybersecurity practices, but also identifies readiness, trust, skills, security, and governance as persistent constraints. Alaskar et al. (2020) find that compatibility, relative advantage, top-management support, and competitive pressure influence BDA adoption in Saudi firms. Mgammal (2024) documents growing AI engagement in Saudi accounting, and Eskandarany (2024) highlights board-level perspectives on AI and machine learning in banking. At the customer and financial-ecosystem level, digital banking, fintech adaptability, open banking, financial inclusion, and cybersecurity studies further show that technological opportunity is inseparable from trust and control (Oladapo et al., 2022; Shabir and Ali, 2022; Mutambik, 2023; Johri and Kumar, 2023).

Against this background, the review develops a Decision Intelligence (DI) framework for enterprise financial risk management. DI is used here as an architectural concept: the coordinated design of data, analytics, rules, human judgment, governance, and feedback around consequential decisions. The paper does not treat DI as a replacement for ERM or management responsibility. Instead, it positions DI as the connective layer through which BDA can strengthen risk sensing, forecasting, prioritization, treatment, escalation, and learning. The resulting framework is intended for large Saudi corporations across banking and nonfinancial sectors where financial exposures span liquidity, credit, market, counterparty, fraud, cyber-financial, operational, and strategic dimensions.

2. Aim of the Study

The study aims to synthesize contemporary evidence on BDA, AI-enabled financial risk analytics, ERM, explainability, governance, and Saudi digital-finance transformation in order to develop an integrated Decision Intelligence Framework for enterprise financial risk management under Saudi Vision 2030. The central analytical purpose is to explain how enterprises can move from fragmented predictive tools toward a governed, closed-loop system in which data are converted into risk intelligence, risk intelligence informs explicit decisions, and decision outcomes are monitored to improve models, controls, and managerial judgment.

3. Research Objectives

The review pursues five objectives. First, it identifies the organizational and technological capabilities through which BDA contributes to decision quality and enterprise performance. Second, it evaluates how machine learning and advanced analytics are being used across credit, fraud, liquidity-related, operational, and broader financial-risk tasks. Third, it examines explainability, data governance, model-risk, cybersecurity, and human-oversight requirements that constrain responsible use of analytical models. Fourth, it synthesizes Saudi-specific evidence on digital banking, fintech, AI, BDA adoption, and financial inclusion to establish contextual requirements for Vision 2030-aligned implementation. Fifth, it integrates these findings into a Decision Intelligence Framework and derives a research agenda for empirical validation in large Saudi enterprises.

4. Research Questions

The review addresses four questions. RQ1 asks which BDA capabilities most consistently support high-quality enterprise decisions. RQ2 asks how advanced analytics can strengthen financial-risk identification, prediction, prioritization, and response without weakening transparency or accountability. RQ3 asks which governance and organizational mechanisms are required to convert analytical outputs into auditable risk decisions. RQ4 asks how these mechanisms should be configured for large Saudi enterprises operating within the digitalization, resilience, and financial-sector development priorities associated with Vision 2030.

5. Review Methodology

A structured integrative review design was selected because the research question spans several mature but weakly connected literatures rather than a single narrowly defined intervention. The method combines systematic search discipline with interpretive synthesis, enabling comparison of empirical, conceptual, and review studies across information systems, finance, risk management, banking, analytics, and Saudi digital transformation. The uploaded Springer article was used only as a structural and academic-writing reference; its topic, empirical content, wording, data, and figures were not reused. Its organization demonstrates a progression from contextual introduction and literature synthesis toward methodological explanation, visual frameworks, results or discussion, and limitations, which informed the present manuscript's logical sequencing rather than its substantive claims.

The review search strategy targeted Scopus, Web of Science, ScienceDirect, SpringerLink, Wiley Online Library, Emerald Insight, Taylor & Francis, IEEE Xplore, and publisher-indexed journal pages. Search strings combined terms including “big data analytics capability,” “decision making,” “enterprise risk management,” “financial risk,” “machine learning,” “credit risk,” “fraud detection,” “explainable

AI," "model governance," "banking analytics," "Saudi Arabia," "fintech," "digital banking," "open banking," and "Vision 2030." Priority was given to studies published from 2020 through 2025, while a limited number of earlier publication dates embedded in 2020 issue releases were retained where they directly supported the contemporary BDA-capability stream. The final reference set contains exactly 30 peer-reviewed journal articles, with bibliographic details and DOI links checked against publisher pages or equivalent reliable records.

Inclusion criteria required a clear relationship to at least one of four domains: BDA capability and decision performance; AI or machine learning for financial-risk tasks; ERM governance and performance; or Saudi financial-sector and enterprise digital transformation. Studies also needed identifiable peer-reviewed journal publication details and a verifiable DOI. Exclusion criteria removed conference-only publications, practitioner commentary, unverifiable outlets, non-peer-reviewed reports, papers without sufficient relevance to enterprise decision processes, and sources for which bibliographic or DOI details could not be confidently confirmed. Government Vision 2030 materials were consulted only to understand policy context and were not counted among the 30 peer-reviewed references.

Screening proceeded in stages without fabricating numerical flow counts. Titles and abstracts were first assessed for conceptual relevance. Potentially useful articles were then examined for method, context, constructs, findings, limitations, and direct relevance to the framework. Quality assessment considered journal provenance, transparency of design, sample or data description, appropriateness of analytical methods, consistency between evidence and conclusions, and acknowledged limitations. Review articles were used to map broad evidence; empirical studies were used to test whether themes such as analytics capability, explainability, governance, or Saudi readiness were supported in applied settings.

Data extraction used a thematic matrix recording research domain, unit of analysis, analytical technology, risk or decision target, enabling capabilities, governance requirements, and reported limitations. Synthesis followed an abductive approach. Initial categories were derived from ERM and analytics concepts, but categories were revised when recurring evidence indicated stronger cross-study mechanisms. Five themes emerged: analytics capability as an organizational system; financial-risk prediction and anomaly detection; explainability and model governance; decision orchestration and ERM integration; and Saudi-context implementation. Differences in sector, sample, outcome measures, and methodology prevented meaningful meta-analysis, so the review does not estimate pooled effect sizes. Instead, it develops a conceptual framework based on convergent mechanisms and explicitly treats causal strength as uncertain where evidence is cross-sectional or context-specific.

6. Thematic Literature Review and Critical Analysis

6.1 Big Data Analytics capability and decision quality. The most consistent finding across the BDA literature is that analytics value is capability-based rather than tool-based. Yasmin et al. (2020) show that infrastructure, management, and human-resource capabilities are interdependent, while Mikalef et al. (2020) demonstrate that BDA capability improves performance indirectly through dynamic and operational capabilities. Upadhyay and Kumar (2020) add that analytical knowledge must be reinforced by organizational culture. These findings challenge technology-first implementations in which enterprises purchase data platforms but leave decision rights, skills, incentives, and business processes unchanged. Shamim et al. (2020) directly connect analytics capability with decision-making performance, and Awan et al. (2021) show that data-driven insight improves decision quality. Huynh et al. (2023), however, caution that BDA-capability research remains conceptually inconsistent and heavily dependent on survey measures. The implication for financial risk is important: enterprises should not equate platform maturity with decision maturity. A robust financial-risk capability requires traceable data lineage, domain expertise, analytical engineering, managerial interpretation, and the ability to embed outputs into specific risk decisions.

Banking studies reinforce this systems view. Al-Dmour et al. (2023) find a positive relationship between BDA practices and bank performance, while identifying organizational factors as especially influential. Abd Aziz et al. (2023) similarly report that BDA capability in Malaysian banking comprises multiple tangible, intangible, and human-skill resources. A four-stage Delphi study of banking applications identifies fraud detection and credit-risk analysis among the most important uses of big data and highlights information silos as a major implementation barrier (Soltani Delgosha et al., 2021). Together, these studies suggest that enterprise financial-risk analytics should be designed around an integrated data fabric rather than separate departmental repositories.

6.2 Advanced analytics for financial-risk sensing and prediction. Contemporary financial-risk analytics is strongest where risk can be represented as repeated classification, ranking, anomaly, or forecasting problems. Shi et al. (2022) document extensive machine-learning development in credit risk and show why model selection must consider data characteristics, interpretability, and evaluation design rather than headline accuracy. Milana (2021) surveys AI applications across finance and identifies opportunities in forecasting, advisory services, risk mitigation, and market analysis, while emphasizing that AI creates new risks arising from data, algorithm choice, and human interpretation in practice today.

Fraud research makes the trade-offs particularly visible. Hilal et al. (2022) show that anomaly detection has shifted from predominantly supervised approaches toward semi-supervised and unsupervised methods that can detect previously unseen behavior. Ali et al. (2022) find widespread use of support-vector machines and neural networks but note unresolved issues involving class imbalance, evolving fraud patterns, and evaluation. Ashtiani and Raahemi (2022) show how machine learning and data mining can strengthen financial-statement fraud detection, whereas Cherif et al. (2023) identify continuing needs for scalable learning, feature engineering, and technologies capable of dealing with disruptive payment environments. Goecks et al. (2022) extend the problem to anti-money-laundering and financial-fraud detection, reinforcing the importance of pattern recognition across complex transaction networks.

These findings support a layered risk-analytics architecture rather than a single enterprise model. Credit, fraud, market, liquidity, counterparty, and operational risks have different labels, horizons, error costs, and intervention mechanisms. Decision Intelligence therefore requires risk-specific models but enterprise-level orchestration. A high false-negative cost in fraud, for example, may justify sensitive anomaly detection followed by investigation, while a treasury liquidity decision may require scenario distributions, stress assumptions, and explicit funding constraints. The analytical layer should preserve such differences while enabling portfolio-level aggregation.

6.3 Explainability, transparency, and model governance. Advanced models can improve predictive discrimination while reducing transparency. Bussmann et al. (2021) show how explainable machine learning can support credit-risk management by making complex relationships interpretable. Dastile and Celik (2021) similarly demonstrate techniques for explaining deep-learning credit scoring, and de Lange et al. (2022) combine LightGBM with SHAP to improve both predictive performance and interpretability in bank credit assessment. These studies do not imply that post-hoc explanations eliminate model risk. Instead, they show that explanations can provide evidence for review, challenge, and communication.

Explainability must therefore be integrated with broader governance. A financial-risk decision requires information about data provenance, model version, calibration date, confidence or uncertainty, key drivers, applicable limits, and the authority responsible for action. The need is reinforced by evidence that ERM effectiveness depends on governance architecture. Malik et al. (2020) find that ERM effectiveness and a structurally strong board-level risk committee are associated with firm performance. Saeidi et al. (2021) show that information technology and knowledge can strengthen the ERM-performance relationship, while Chairani and Siregar (2021) connect ERM with financial performance and firm value in an ESG context. Al-Nimer et al. (2021) further link risk-management practices, business-model innovation, and performance. These studies collectively suggest that analytics should enhance, not bypass, existing governance bodies.

6.4 Saudi digital-finance context. Saudi evidence points to rapid technology adoption combined with institutional and behavioral dependencies. Alaskar et al. (2020) show that top-management support, compatibility, relative advantage, and competitive pressure influence BDA adoption in Saudi firms. Mgammal (2024) reports that AI awareness, usage, and engagement are associated with changes in accounting procedures and efficiency, indicating growing organizational readiness for AI-assisted financial processes. Eskandarany (2024) adds a board-level banking perspective and highlights the importance of governance in AI and machine-learning adoption.

Financial-service studies show that the decision environment is also changing externally. Oladapo et al. (2022) find that knowledge, attitude, and subjective norms shape fintech adaptability among Islamic-bank customers in Saudi Arabia and Malaysia. Shabir and Ali (2022) document continuing inclusion differences across demographic groups, making fairness and accessibility relevant to digital financial decisions. Mutambik (2023) shows that customer experience in open banking influences loyalty intentions, while Johri and Kumar (2023) identify cybersecurity awareness and technical support as significant issues in Saudi digital banking. The consequence for enterprise financial-risk management is that risk signals increasingly originate outside conventional finance systems: API activity, customer behavior, cyber events, third-party ecosystems, digital channels, and platform dependencies can all have financial consequences.

Table 1 synthesizes these literatures. The evidence supports a move from periodic risk reporting toward continuous decision cycles, but it also exposes a recurrent weakness: studies often examine analytics, governance, or adoption separately. The proposed DI framework addresses this separation by making the decision itself the organizing unit of design.

Table 1. Cross-theme synthesis of evidence for Decision Intelligence in enterprise financial risk management

Evidence theme	**Representative evidence**	**Critical synthesis**	**Implication for Saudi enterprises**
BDA capability & decision quality	Yasmin et al. (2020); Mikalef et al. (2020); Shamim et al. (2020); Huynh et al. (2023)	Value depends on complementary data, skills, management routines and decision integration—not	Assess decision maturity alongside platform maturity; define ownership and data lineage.

Evidence theme	Representative evidence	Critical synthesis	Implication for Saudi enterprises
		platforms alone.	
Financial-risk analytics	Shi et al. (2022); Hilal et al. (2022); Cherif et al. (2023); Goecks et al. (2022)	Credit and fraud tasks benefit from ML, but error costs, drift, imbalance and adversarial behavior require risk-specific controls.	Use separate models by risk type, with enterprise-level exposure aggregation and escalation.
Explainability & model governance	Bussmann et al. (2021); Dastile & Celik (2021); de Lange et al. (2022)	Explanations support challenge and audit but do not remove model risk; provenance, versioning and validation remain essential.	Require audience-appropriate explanations, model registries and independent validation for material decisions.
ERM governance	Malik et al. (2020); Chairani & Siregar (2021); Saeidi et al. (2021); Al-Nimer et al. (2021)	Risk performance is shaped by governance architecture, board oversight, information technology and organizational knowledge.	Link analytical thresholds to risk appetite, approval rights, committees and policy controls.
Saudi digital-finance context	Alaskar et al. (2021); Mgammal (2024); Eskandarany (2024); Mutambik (2023)	Rapid digital adoption is accompanied by readiness, cybersecurity, trust, inclusion and governance dependencies.	Stage implementation, preserve human accountability, and incorporate cyber/platform signals into financial-risk monitoring.

7. Proposed Decision Intelligence Framework

The proposed framework contains six connected layers: data foundation, analytics, risk fusion, decision orchestration, governance and human oversight, and outcome learning. Figure 1 represents the end-to-end flow. The data foundation integrates enterprise resource planning, treasury, receivables, payments, procurement, customer, market, macroeconomic, cyber, and third-party data while enforcing ownership, metadata, quality rules, access controls, and lineage. This layer responds directly to the information-silo problem identified in banking analytics and to the broader BDA-capability evidence that infrastructure alone is insufficient unless it is governed and usable.

The analytics layer hosts risk-specific models for forecasting, classification, anomaly detection, stress testing, network analysis, and scenario simulation. Models generate probability estimates, ranges, alerts, and explanations rather than autonomous final decisions. The risk-fusion layer normalizes outputs against common exposure definitions, risk taxonomy, materiality thresholds, and risk appetite. Its purpose is to prevent local model optimization from producing globally inconsistent actions. For example, a model recommending aggressive credit growth should be reconciled with liquidity capacity, concentration limits, counterparty exposures, and strategic capital priorities.

Decision orchestration converts fused risk signals into explicit decision objects. Each object records the decision question, available alternatives, expected financial impact, risk constraints, recommended action, explanation, required approvals, and escalation path. This is the defining contribution of the framework. Analytics becomes operational only when linked to a decision with an accountable owner and a controllable action. Human oversight remains mandatory for material decisions, model exceptions, low-confidence cases, ethical concerns, or conflicts with policy. Automated execution is limited to clearly bounded routine decisions whose thresholds, controls, rollback rules, and monitoring have been formally approved.

The outcome-learning layer closes the loop. Actual defaults, fraud outcomes, cash-flow deviations, hedge effectiveness, covenant events, loss incidents, and management overrides are captured and compared with predicted outcomes. These data support recalibration, drift detection, policy adjustment, and review of human decisions. Figure 2 presents this continuous sense-predict-decide-act-learn cycle, with governance operating across all stages rather than as a final compliance checkpoint.

Table 2 converts the framework into implementable control requirements. Its central proposition is that a DI-enabled risk system should be evaluated on four dimensions simultaneously: predictive usefulness, decision timeliness, explainability and auditability, and realized risk-adjusted outcomes. A model that is statistically accurate but too slow for treasury action, impossible to explain to a credit committee, or disconnected from actual loss reduction should not be treated as effective decision intelligence.

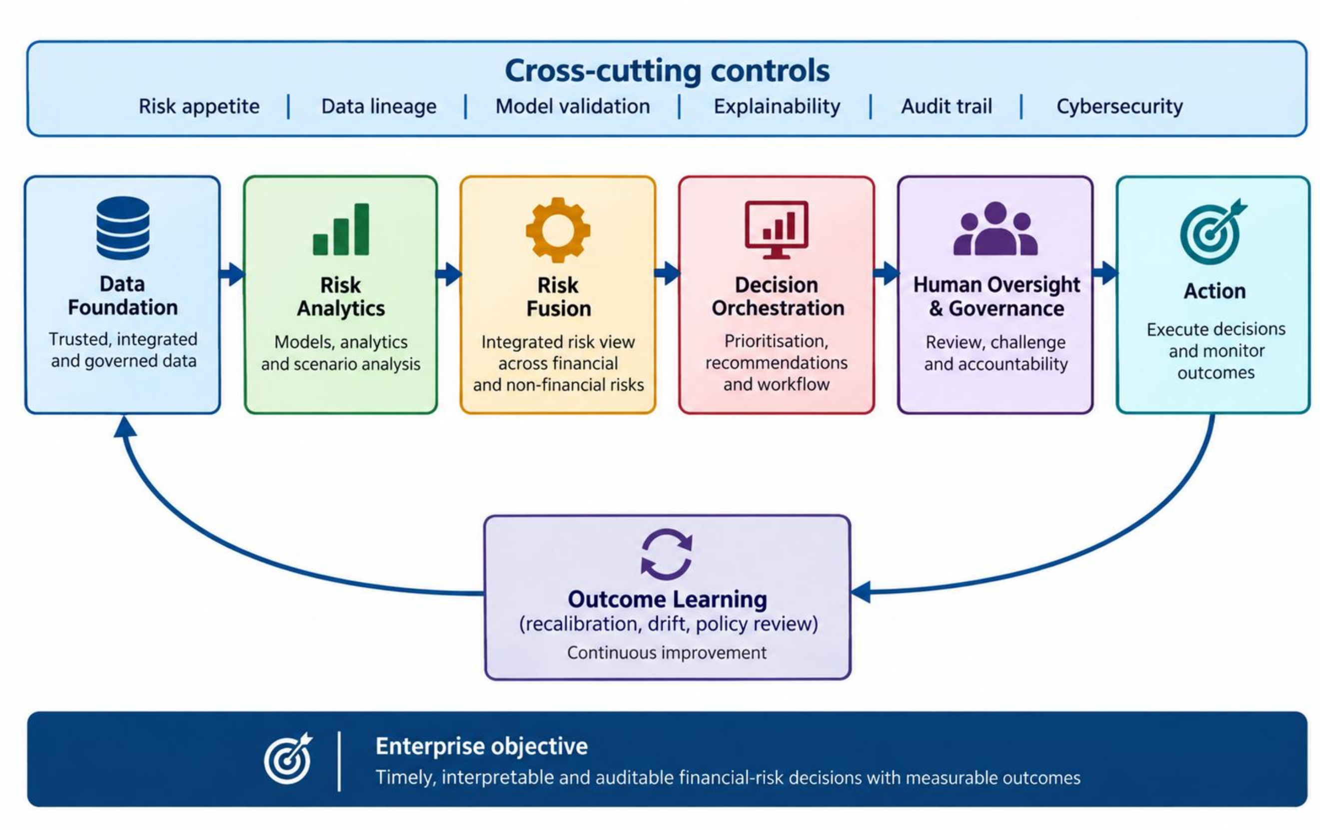

Figure 1. Proposed Decision Intelligence Framework integrating Big Data Analytics with enterprise financial risk governance.

Figure 2. Closed-loop Decision Intelligence lifecycle: sense, predict, decide, act and learn under continuous governance.

Table 2. Operational design requirements for the proposed Decision Intelligence Framework

Layer	**Primary function**	**Key controls**	**Illustrative financial-risk outputs**
Data foundation	Integrate internal, external and near-real-time data	Ownership, quality rules, metadata, access, lineage, cybersecurity	Validated exposure, transaction, market, treasury and third-party data
Risk analytics	Generate forecasts, classifications, anomalies and scenarios	Model documentation, validation, calibration, drift and bias testing	Default probabilities, fraud alerts, cash-flow forecasts, stress scenarios
Risk fusion	Reconcile model outputs	Common taxonomy,	Portfolio-level risk priorities

Layer	Primary function	Key controls	Illustrative financial-risk outputs
	with enterprise exposure and risk appetite	materiality, concentration and capital/liquidity constraints	and cross-risk conflicts
Decision orchestration	Translate signals into explicit alternatives and recommendations	Named decision owner, approval rights, thresholds, escalation and rollback rules	Limit changes, funding actions, investigation cases, hedging or collection actions
Human oversight & governance	Challenge, approve or override material recommendations	Explainability, audit trail, segregation of duties, committee oversight	Approved, modified or rejected actions with rationale
Outcome learning	Compare predicted and realized outcomes	Performance monitoring, override analysis, recalibration and policy review	Loss avoided, decision latency, false-alert cost, liquidity resilience, capital efficiency

8. Discussion

The synthesis indicates that the principal bottleneck in analytics-enabled financial risk management is not model availability but organizational conversion. BDA studies repeatedly show that performance gains depend on complementary management, skills, routines, and culture. Financial-machine-learning studies show that predictive methods are increasingly capable but vulnerable to opacity, drift, imbalance, and context sensitivity. ERM studies show that governance structures influence whether risk practices create value. Saudi studies show strong momentum in digital adoption alongside continuing needs for trust, cybersecurity, skills, and institutional readiness. Decision Intelligence provides a unifying explanation: value emerges when these components are designed around recurring decisions rather than deployed as independent initiatives.

This perspective also clarifies the relationship between DI and ERM. ERM defines governance, risk appetite, taxonomy, escalation, and accountability at enterprise level. DI operationalizes those principles through data and analytical workflows at decision level. The two are therefore complementary. ERM without DI can remain periodic and descriptive; DI without ERM can become technically powerful but strategically incoherent. The framework links risk-appetite statements to machine-readable thresholds, embeds model outputs into approval workflows, and captures overrides and realized outcomes for subsequent review.

The Saudi context adds a strategic dimension. Financial Sector Development Program priorities include a more diversified, resilient, and technologically advanced financial system, while enterprise digitalization increases both opportunity and exposure. Large Saudi corporations are often participants in complex ecosystems involving banks, government entities, international suppliers, capital markets, digital platforms, and major investment programs. Their financial-risk systems therefore need to combine conventional accounting and treasury data with external and near-real-time signals. However, the framework should not be interpreted as an argument for maximal automation. The literature on explainability and governance supports selective automation, stronger documentation, and human challenge in material decisions.

A further implication concerns data ethics and inclusion. Saudi financial-inclusion and fintech studies show that access, trust, knowledge, and customer experience vary across groups. If enterprise models rely on behavioral or alternative data, model governance should test whether proxy variables create unjustified differences in credit, pricing, fraud investigation, or service decisions. Explainability should therefore serve not only managers and regulators but also internal audit, model validators, customers where relevant, and affected business units. Audience-dependent explanation is part of accountable decision architecture rather than a cosmetic visualization feature.

Finally, the framework changes how analytics success should be measured. Conventional projects emphasize area-under-the-curve, accuracy, precision, recall, or forecast error. Those metrics remain necessary but incomplete. DI evaluation should add decision latency, override frequency, loss avoided, false-alert investigation cost, capital efficiency, liquidity resilience, policy compliance, and realized return relative to risk. Such measures make it possible to distinguish technically impressive models from systems that genuinely improve enterprise financial decisions.

9. Research Gaps and Future Research

Five gaps deserve priority. First, there is limited empirical work that treats analytics, ERM governance, and decision workflows as one system. Future studies should test whether integrated DI architectures outperform stand-alone dashboards or models in decision speed, consistency, and realized loss reduction. Second, Saudi evidence is growing but remains fragmented across banking customers, accounting professionals, technology adoption, and individual financial services. Longitudinal studies in large Saudi corporations should examine treasury, credit, procurement-finance, project-finance, and counterparty decisions using operational data rather than perception measures alone.

Third, model-risk research should move beyond explanation demonstrations toward governance effectiveness. Experiments could compare different explanation formats for credit committees, chief risk officers, internal auditors, and business managers, testing whether explanations improve challenge quality without creating false confidence. Fourth, multi-risk interaction remains underdeveloped. Financial losses increasingly arise from connected events, such as a cyber incident that interrupts payments, creates liquidity pressure, damages customer confidence, and triggers regulatory cost. Graph analytics and causal methods should therefore be tested for enterprise risk propagation, not only isolated prediction.

Fifth, research should evaluate how DI aligns with Saudi regulatory and organizational requirements as data-sharing ecosystems expand. Open banking, cloud platforms, fintech partnerships, and AI use create new dependencies in data residency, third-party risk, cybersecurity, privacy, and model accountability. Future work should develop validated maturity scales for Saudi enterprises covering data governance, analytics, decision integration, human oversight, and outcome learning. Comparative studies across sectors would show whether the framework requires different control intensity in banking, energy, telecom, logistics, healthcare, or large project organizations.

10. Practical, Managerial, and Policy Implications

For managers, implementation should begin with a portfolio of high-value risk decisions rather than a generic enterprise AI program. Candidate decisions include counterparty-limit changes, collection prioritization, short-term liquidity actions, hedge adjustments, supplier credit exposure, fraud escalation, and capital allocation. Each decision should have a named owner, required data, analytical method, risk limits, approval rules, and measurable outcome. This approach makes technology investment traceable to risk and financial value.

For chief risk officers and finance leaders, the framework requires joint ownership with data and technology functions. A centralized model registry should document purpose, data lineage, training period, validation results, thresholds, limitations, approved users, and monitoring status. Material models should be independently validated and periodically challenged. Override behavior should be monitored because frequent overrides may indicate model weakness, poor change management, or misaligned risk appetite. Conversely, zero overrides should not automatically be interpreted as success if users are merely deferring to opaque recommendations.

For boards and executive committees, governance should focus on decision rights and aggregate exposure rather than technical detail alone. Reporting should show where algorithms influence material financial decisions, what controls constrain automation, how model performance is changing, and whether realized outcomes remain within risk appetite. Policy bodies and regulators can encourage responsible innovation by emphasizing traceability, explainability proportional to decision materiality, cybersecurity, third-party assurance, and evidence of human accountability. Such principles support digital transformation while preserving resilience, which is consistent with the broader Saudi objective of developing an advanced and dependable financial ecosystem.

11. Limitations

This review has several limitations. It synthesizes heterogeneous literatures and therefore cannot establish a single causal effect of DI or BDA on financial-risk outcomes. Many cited BDA and adoption studies are cross-sectional and rely on managerial perceptions, which can overstate capability or performance relationships. The Saudi-specific evidence is still smaller than the global literature and is concentrated in banking, fintech, accounting, and technology-adoption settings. The proposed framework is therefore conceptual and requires field validation before being treated as a prescriptive standard. The review also prioritizes English-language peer-reviewed journal literature with verifiable DOIs, which may exclude relevant Arabic studies, industry evidence, and confidential enterprise implementations. Finally, rapid development in generative AI, agentic systems, privacy-enhancing technologies, and regulatory expectations means that governance requirements will continue to evolve.

12. Conclusion

The review concludes that Big Data Analytics can strengthen enterprise financial risk management only when embedded in a governed decision system. Contemporary evidence supports the value of analytics capabilities, machine learning for credit and fraud tasks, explainability, ERM governance, and digital financial innovation, but these streams are usually studied separately. The proposed Decision Intelligence Framework integrates them through a closed loop: governed data feed risk-specific analytics; analytical outputs are fused against enterprise exposures and risk appetite; recommendations become explicit decision objects; accountable humans approve, challenge, or override actions; and realized outcomes update models and policies.

For large Saudi corporations, this architecture is well aligned with an economy experiencing rapid digitalization, expanding fintech and open-banking ecosystems, large-scale investment, and increasing demand for resilient financial management under Vision 2030. The framework does not assume that more automation is inherently better. Its emphasis is disciplined augmentation: faster sensing, better forecasting, clearer explanations, stronger auditability, and accountable action. The most important implementation principle is therefore to design from the decision backward. Enterprises should first define the material risk decision, its owner, limits, evidence needs, and consequences; only then should they select data and analytical methods. Future empirical research should test whether this decision-centered architecture improves realized financial outcomes, resilience, and governance quality across Saudi sectors. Implementation should also be evaluated as an organizational learning process, because reliable risk decisions depend on continuous coordination among finance, risk, data, technology, audit, and business teams. Such coordination can expose hidden assumptions, improve escalation discipline, strengthen institutional knowledge, and help organizations distinguish genuine analytical value from temporary model performance gains across changing market conditions.

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