



AI-Enabled Financial Risk Management Framework for Debt Financing Decisions in Saudi Enterprises under Vision 2030

Qasim Majeed^{1*}

¹Group Head - FP&A, ESOM Holding, Riyadh, Saudi Arabia

*Corresponding Author

Qasim Majeed

Group Head - FP&A, ESOM
Holding, Riyadh, Saudi Arabia

Article History

Received: 04.08.2026

Accepted: 29.09.2026

Published: 08.10.2026

Abstract: Saudi Arabia's Vision 2030 has increased the strategic importance of diversified and sustainable financing for enterprises participating in infrastructure, energy, industrial, technology, tourism and service-sector expansion. At the same time, debt financing exposes firms to interconnected credit, liquidity, refinancing, interest-rate, cash-flow, project and concentration risks. Conventional ratio analysis and management forecasting remain essential, but periodic and predominantly historical approaches may not fully exploit the financial, operational and market data now generated by enterprise resource planning, treasury, banking and project-management systems. Artificial intelligence (AI), machine learning (ML), predictive analytics and explainable artificial intelligence (XAI) can extend established finance practice by identifying nonlinear risk patterns, improving early-warning capability and supporting forward-looking debt-capacity assessment. This paper develops an AI-enabled financial risk management framework for debt financing decisions in Saudi enterprises. It uses an integrative structured review of recent peer-reviewed literature on corporate default prediction, credit risk, financial distress, loss given default, explainable AI and financial risk analytics, combined with official Saudi sources on financial-sector and debt-market development. The resulting framework comprises six layers: integrated data, AI-supported risk identification, predictive debt-capacity analysis, scenario and stress testing, explainable decision intelligence, and governance with continuous monitoring. The framework treats AI as an augmentation of professional judgement rather than an autonomous financing authority. It proposes practical metrics, a governance workflow and implementation priorities for CFOs, FP&A teams, treasury functions, risk managers and boards. The study contributes by connecting AI-based risk analytics specifically to corporate debt financing in the Saudi Vision 2030 context while explicitly addressing explainability, data governance, model risk and human accountability.

Keywords: Artificial Intelligence, Financial Risk Management, Debt Financing, Saudi Arabia, Vision 2030, Machine Learning, Predictive Analytics, Explainable AI, Liquidity Risk, Credit Risk, FP&A.

Copyright © 2026 The Author(s): This is an open-access article distributed under the terms of the Creative Commons Attribution 4.0 International License (CC BY-NC 4.0) which permits unrestricted use, distribution, and reproduction in any medium for non-commercial use provided the original author and source are credited.

1. INTRODUCTION

Saudi Arabia is undertaking a large-scale economic transformation under Vision 2030, with

policy programs designed to deepen financial markets, strengthen private-sector participation and support investment in non-oil activities. Within the

Citation: Majeed, Q. (2026). E AI-Enabled Financial Risk Management Framework for Debt Financing Decisions in Saudi Enterprises under Vision 2030; *Glob Acad J Econ Buss*, 8(5), 1628-1640. <https://doi.org/10.36348/gajeb.2026.v08i05.050>
1628

Financial Sector Development Program (FSDP), the debt capital market is treated as an important alternative funding channel for both public and private-sector entities. The FSDP Annual Report 2024 reported a debt-market size equivalent to 20.76% of GDP, compared with a 14% baseline and a 24.1% target for 2025 (Financial Sector Development Program [FSDP], 2025). This direction matters for corporate finance because a broader debt market can expand the menu of financing instruments available to Saudi enterprises, including bank loans, syndicated facilities, sukuk, bonds, project finance and structured facilities.

The expansion of financing options does not remove financial risk; it makes risk assessment more important. A corporation may be profitable at the time financing is raised yet later face pressure from delayed customer collections, project cost overruns, refinancing concentration, higher benchmark rates, foreign-currency mismatches or declining operating margins. The Saudi Central Bank reported that corporate credit increased by 13.2% in 2023 to SAR 1,329 billion, making the corporate segment a major driver of banking-credit growth (Saudi Central Bank [SAMA], 2024). Higher credit availability can support productive investment, but it also increases the value of robust debt-capacity analysis, liquidity planning, covenant forecasting and early-warning systems.

Traditional financial-risk analysis relies on well-established tools such as leverage, interest coverage, debt-service coverage, liquidity ratios, cash-flow forecasts, sensitivity analysis and management judgement. These tools remain indispensable because they translate business performance into understandable measures of debt sustainability. However, traditional analysis can be constrained when relationships are nonlinear, when data arrive at different frequencies, or when risk emerges through interacting operational variables. Recent research shows that machine-learning methods can improve corporate default prediction in some contexts by capturing nonlinear effects and interactions that standard statistical models may not fully represent (Moscattelli *et al.*, 2020; Sigrist & Leuenberger, 2023). Deep-learning and ensemble methods have also been applied to corporate failure, loss-given-default and medium-term distress forecasting (Alam *et al.*, 2021; Olson *et al.*, 2021; Perboli & Arabnezhad, 2021).

AI adoption in finance nevertheless raises governance questions. A model that is accurate but opaque may be difficult for a CFO, audit committee, lender or board to rely on. Explainable AI has therefore become central to financial applications because high-impact decisions require traceability, challenge and accountability (Bussmann *et al.*, 2021;

Weber *et al.*, 2024; Cerneviene & Kabasinskas, 2024). The central research problem is not whether AI should replace corporate-finance judgement, but how AI can be embedded in a controlled architecture that improves prediction while retaining transparent decision rights.

This paper addresses that problem by proposing an AI-enabled financial risk management framework for debt financing decisions in Saudi enterprises. The framework is intended for organisations with meaningful debt exposure and sufficient financial and operational data, particularly large or diversified groups, project-based enterprises and firms considering debt-funded expansion under the evolving Saudi capital-market environment. The paper does not present invented empirical data. Instead, it develops a conceptual and practice-oriented framework from peer-reviewed evidence and official Saudi institutional sources, identifies research propositions and defines a pathway for future empirical validation.

2. Aim, Objectives and Research Questions

The aim of this study is to develop a comprehensive AI-enabled financial risk management framework that can improve the quality, timeliness and transparency of debt financing decisions in Saudi enterprises under Vision 2030.

Five objectives guide the study. First, it identifies the financial risks most relevant to corporate debt financing, with particular attention to credit, liquidity, refinancing, interest-rate, cash-flow and project risks. Second, it examines how AI and machine-learning methods can complement established financial analysis by improving early-warning, default prediction and forward-looking debt-capacity assessment. Third, it evaluates the role of explainability, model validation, data governance and human oversight in high-impact corporate-finance decisions. Fourth, it integrates these elements into a six-layer conceptual framework linked to practical metrics such as Debt/EBITDA, interest coverage ratio (ICR), debt-service coverage ratio (DSCR), liquidity headroom and covenant headroom. Fifth, it develops managerial and research implications relevant to Saudi enterprises and the Kingdom's debt-market development agenda.

The study addresses five research questions: RQ1: Which financial risks should be incorporated in an enterprise-level debt financing decision framework in Saudi Arabia? RQ2: How can AI and machine-learning techniques improve risk identification and prediction compared with exclusively historical analysis? RQ3: How should conventional finance metrics and AI-generated signals be combined in debt-capacity assessment?

RQ4: What explainability, validation and governance controls are necessary for responsible adoption?
 RQ5: What empirical research is required to validate an AI-enabled debt-risk framework in the Saudi corporate environment?

3. Saudi Debt-Market and Financial-System Context

The proposed framework is grounded in the institutional direction of the Saudi financial sector. The FSDP aims to develop an advanced capital market, expand financing alternatives and support private-sector growth while maintaining financial stability. Official program data show that the debt market has grown materially relative to the original baseline, although the program's 2025 target indicates further room for development (FSDP, 2025). The Capital Market Authority (CMA) has also published strategic directions for developing the sukuk and debt capital market, including initiatives related to credit-rating access, market liquidity, electronic trading, corporate debt-market infrastructure and connections with international depositories (Capital Market Authority [CMA], 2024). These measures are relevant to corporations because deeper markets can reduce overdependence on a single source of finance and broaden tenor and instrument choice.

The banking system remains important to corporate funding. SAMA's Financial Stability Report 2024 found strong corporate-credit growth in 2023 and described the banking sector as well capitalised. The International Monetary Fund's 2024 Financial

Sector Assessment Program likewise observed that Vision 2030's financial-sector strategy seeks to enable institutions to support private-sector growth, develop advanced capital markets and maintain stability (International Monetary Fund [IMF], 2024). These findings support a balanced interpretation: Saudi enterprises operate in a financial system with expanding capacity and market-development initiatives, but corporate borrowers still need disciplined risk management to ensure that additional debt supports sustainable value creation.

Saudi Arabia also has a significant Islamic-finance dimension. Sukuk provide an important capital-market financing route, and financial-risk conditions can affect sukuk-market development. Boukhatem (2022), using Saudi data, found that exchange-rate stability, foreign-debt stability and debt-service stability were relevant to sukuk-market development. The implication for corporate issuers is that debt structuring cannot be separated from broader financial conditions. Whether the instrument is a conventional facility or a Shariah-compliant sukuk, the issuer must evaluate cash-flow resilience, maturity concentration, pricing, covenants and market access.

The Saudi context therefore supports an enterprise-level framework combining corporate finance, risk management and digital analytics. As financing choices broaden, issuer readiness will depend increasingly on forecasting, information quality and governance.

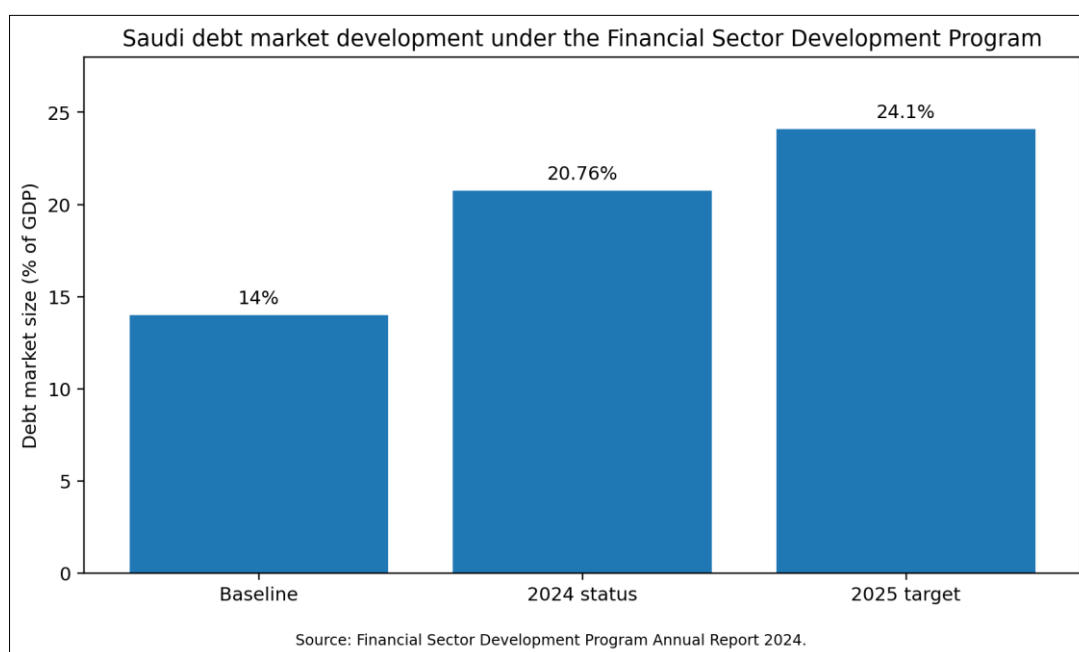


Figure 1: Saudi debt market size as a percentage of GDP: baseline, 2024 status and 2025 target
Source: FSDP Annual Report 2024

Table 1: Selected Saudi financial-sector indicators relevant to corporate debt risk

Indicator	Observation	Period	Decision relevance
Debt market size / GDP	20.76% (baseline 14%; 2025 target 24.1%)	Q4 2024	Shows development of debt-market depth and financing alternatives.
Corporate bank credit	SAR 1,329 billion; +13.2%	2023	Highlights scale and growth of corporate borrowing through banks.
Bank capital adequacy	20.1%	2023	Indicates banking-system capital strength, not individual borrower quality.
FSDP private-sector credit / GDP	69%	2024 status	Signals increasing financial intermediation and importance of borrower risk discipline.

Sources: FSDP Annual Report 2024; SAMA Financial Stability Report 2024. The indicators describe the financial environment and are not a measure of any individual enterprise's creditworthiness.

4. Theoretical Foundations

The conceptual framework draws first on corporate capital-structure theory. Trade-off and pecking-order perspectives emphasise that debt decisions form part of a broader capital structure shaped by distress costs, strategic flexibility, information asymmetry and financing alternatives. The present study does not test these theories, but uses them to frame debt as a portfolio decision rather than an isolated transaction.

The second foundation is enterprise risk management. Debt sustainability depends on multiple risks that interact. Credit deterioration may originate in operating weakness; liquidity pressure may be triggered by working-capital delays; refinancing exposure may become critical when maturities coincide with adverse market conditions. An integrated approach is therefore superior to a fragmented set of risk indicators. The proposed framework treats debt risk as an outcome of interacting financial, operational, project and market variables rather than a single ratio.

The third foundation is decision intelligence. AI is useful when it improves the sequence from data to prediction, interpretation and action. Machine learning can identify patterns, but the value of those patterns depends on whether managers can connect them to a financing decision. Explainability research in finance indicates that feature importance, SHAP values, rule-based explanations and related tools can help translate complex predictions into information that decision-makers can challenge and use (Bussmann *et al.*, 2021; Yeo *et al.*, 2025; Khan *et al.*, 2025). Accordingly, the proposed model is designed as a human-in-the-loop system in which algorithms generate evidence and management retains accountability.

5. REVIEW METHODOLOGY

An integrative structured-review approach was used because the research question crosses corporate finance, financial risk, machine learning, explainable AI and the Saudi financial environment. The study synthesises recent peer-reviewed research

and official institutional evidence rather than conducting a meta-analysis. A meta-analysis would be inappropriate because the underlying studies use different countries, borrower populations, outcome definitions, algorithms, horizons and performance metrics.

The academic search logic focused on combinations of terms including artificial intelligence, machine learning, corporate default, financial distress, credit risk, loss given default, debt financing, explainable AI, predictive analytics, cash-flow risk and financial risk management. Priority was given to studies published from 2020 onward in peer-reviewed journals, supplemented by official Saudi sources on the debt market, banking system and financial-sector development. The review gives particular weight to research that compares machine-learning methods with conventional approaches, addresses interpretability or governance, or has direct relevance to corporate failure and debt risk.

Inclusion criteria required a clear link to financial-risk assessment, corporate distress/default, credit analysis, model explainability or financial decision support. Studies focused exclusively on unrelated AI applications were excluded. Official Saudi sources were included where they provided market structure, program targets or financial-system context. The review does not fabricate article-screening counts because a formal reproducible database export was not undertaken for this conceptual paper. This limitation is stated explicitly to distinguish the present integrative review from a PRISMA-style systematic review with a registered search protocol.

Evidence was synthesised into six recurring themes: data integration, early-warning risk identification, predictive debt-capacity assessment, scenario and stress testing, explainability, and governance/continuous monitoring. These themes became the six layers of the proposed framework. The approach is consistent with recent reviews that emphasise both the predictive potential and

implementation challenges of machine learning in financial risk management (Tian *et al.*, 2024; Montevechi *et al.*, 2024; Theodorakopoulos *et al.*, 2025).

6. Financial Risks Relevant to Debt Financing

Credit and default risk are the most visible debt-related risks because they concern the firm's ability to meet contractual obligations. However, default is usually the final outcome of earlier deterioration. Warning signs may include declining profitability, weaker operating cash flow, rising leverage, slower collections, margin compression, negative project variance, covenant pressure or repeated forecast underperformance. Machine-learning studies demonstrate that these variables can interact nonlinearly, which is one reason algorithmic models can add value to conventional scorecards (Moscatelli *et al.*, 2020; Alam *et al.*, 2021).

Liquidity risk is distinct from profitability. A company can report accounting profit while lacking cash to meet near-term debt service. Debt analysis should therefore monitor cash conversion, receivable ageing, inventory, payable timing, committed facilities, unrestricted cash, minimum operating cash requirements and scheduled principal and interest payments. In project-based businesses, the timing of certified work, customer billing and collection can be more important to short-term debt capacity than annual profit.

Refinancing risk arises when the enterprise depends on future access to capital markets or bank facilities. A company may be solvent on a going-concern basis yet face acute pressure if a large proportion of debt matures in a short window. An AI-enabled framework should therefore include maturity concentration, expected refinancing costs, lender concentration and sensitivity to changes in credit conditions.

Interest-rate risk affects floating-rate facilities directly and fixed-rate borrowers at refinancing. Stress testing should not simply apply a higher rate to current interest expense; it should project the effect on free cash flow, ICR, DSCR, covenant headroom and investment capacity. Foreign-exchange risk should also be included where debt currency differs from the currency of operating cash flows.

Project and operational risks are particularly relevant to Saudi enterprises involved in construction, O&M, energy, real estate and infrastructure. Cost overruns, variation-order delays, supply-chain disruption, project slippage or customer concentration can materially affect cash generation. The framework therefore integrates

project-level indicators into financial-risk assessment rather than relying solely on general-ledger ratios.

Finally, concentration and governance risk can amplify all other risks. Dependence on a small number of customers, lenders, projects or funding instruments reduces resilience. Weak data quality, optimistic forecasts or poorly controlled model overrides can create a false sense of security. Effective debt risk management consequently requires both quantitative analytics and strong control processes.

7. Evidence on AI and Machine Learning in Financial Risk

The empirical literature generally supports the view that machine learning can improve risk prediction in appropriate settings, but it also warns against universal claims. Moscatelli *et al.*, (2020) compared machine-learning and statistical approaches for corporate default forecasting and reported accuracy gains associated with nonlinear modelling. Sigrist and Leuenberger (2023) extended the analysis to multi-period default probabilities and found larger gains for longer horizons, where interaction effects become more important. These findings are relevant to debt financing because corporate decisions are rarely limited to a one-year horizon; lenders and CFOs need to understand risk across the tenor of the facility.

Alam *et al.*, (2021) evaluated deep learning against discrete hazard models for corporate failure prediction and found strong out-of-sample performance in their North American dataset. Perboli and Arabnezhad (2021) developed a machine-learning decision-support approach for medium- and long-term company crisis prediction, showing how predictive models can be connected to policy or management decisions rather than treated as purely technical exercises. Olson *et al.*, (2021) applied multiple machine-learning methods to loss-given-default for corporate debt and highlighted the continuing importance of benchmarking, cross-validation and model monitoring.

The information set also matters. Chen *et al.*, (2023) showed that annual-report text can improve bankruptcy prediction when combined with financial variables. Future corporate-risk systems may therefore use verified narrative information from management reports or covenant documents, subject to confidentiality and reliability controls.

Reviews of financial distress research show that model performance is influenced by preprocessing, class imbalance, feature selection, sample design and evaluation metrics (Kuiziniene *et*

al., 2022). Montevechi *et al.*, (2024) similarly conclude that machine learning has significant potential in credit-risk modelling but requires standardised modelling procedures and interpretability before widespread commercial deployment. Tian *et al.*, (2024) find no single algorithm that is best for all financial-risk contexts; data characteristics and institutional needs should determine model choice.

These findings imply that a Saudi enterprise should not adopt AI because a particular algorithm is fashionable. The appropriate approach is to establish a transparent modelling pipeline, benchmark advanced models against interpretable baselines, evaluate out-of-time performance, and connect outputs to decisions that finance professionals already understand.

Table 2: Selected literature informing the proposed framework

Study	Application	Key evidence	Implication for this framework
Moscatelli <i>et al.</i> , (2020)	Corporate default	ML captured nonlinearities and improved forecasting in the study setting.	Use ML as an incremental layer over statistical benchmarks.
Olson <i>et al.</i> , (2021)	Loss given default	Compared 12 ML methods and stressed monitoring/model uncertainty.	Require benchmarking, out-of-time validation and monitoring.
Alam <i>et al.</i> , (2021)	Corporate failure	Deep learning outperformed a discrete hazard benchmark in the sample.	Complex models may add value when data volume supports them.
Perboli & Arabnezhad (2021)	Company crisis	Connected ML prediction to a decision-support system.	Design outputs around management actions, not scores alone.
Carmona <i>et al.</i> , (2022)	Business failure/XAI	Demonstrated interpretable XGBoost failure prediction.	Use explainability to identify finance-relevant risk drivers.
Sigrist & Leuenberger (2023)	Multi-period default	ML gains increased over longer horizons in their study.	Evaluate risk over the debt tenor, not only one year.
Chen <i>et al.</i> , (2023)	Bankruptcy + annual-report text	Text variables improved several ML models.	Future systems can integrate verified narrative information.
Cerneviciene & Kabasinskas (2024)	XAI in finance	Review found SHAP/feature importance widely used.	Make explainability a core governance layer.

8. Proposed AI-Enabled Financial Risk Management Framework

The proposed framework contains six interdependent layers. Layer 1 is an integrated data foundation. It combines audited and management financial statements, ERP transactions, treasury data, debt schedules, covenant definitions, working-capital information, project indicators and external market variables. A common data dictionary is essential because the same metric can be defined differently across subsidiaries. For example, EBITDA used for management reporting may differ from covenant EBITDA. The framework therefore requires controlled definitions, lineage and reconciliation before modelling begins.

Layer 2 is AI-supported risk identification. The objective is not to forecast default immediately but to identify emerging deterioration. Candidate indicators include falling cash conversion, increasing receivable days, repeated budget misses, deteriorating project margins, rising utilisation of short-term facilities, negative free cash flow, lower interest coverage, covenant compression and

maturity concentration. The system should generate early-warning signals at an agreed frequency, with thresholds calibrated to the enterprise's risk appetite.

Layer 3 is predictive debt-capacity analysis. The model estimates the future distribution of core debt metrics under the base forecast. Debt/EBITDA measures leverage; ICR relates operating earnings to interest expense; DSCR compares cash available for debt service with scheduled debt service; and liquidity headroom compares available cash and committed facilities with forecast requirements. AI is used to forecast the variables feeding these ratios and the probability that a threshold will be breached, rather than replacing the ratios themselves.

Layer 4 is scenario and stress testing. Management specifies economically meaningful shocks such as revenue decline, collection delay, margin compression, interest-rate increases, cost overruns or delayed project completion. Combined stresses are especially important because financial distress often results from interacting shocks. The

framework should calculate the effect on cash, leverage, covenant headroom and refinancing requirements across each scenario.

Layer 5 is explainable decision intelligence. A model output such as 'high risk' has limited value without an explanation. XAI techniques can identify which variables contributed to the prediction and how the risk changes under alternative assumptions. Carmona *et al.*, (2022) demonstrate the usefulness of interpreting XGBoost business-failure predictions, while Bussmann *et al.*, (2021) show how explainability can be incorporated in credit-risk management. The enterprise should present model drivers in finance language: for example, 'risk

increased primarily because of maturity concentration, lower forecast cash conversion and weaker interest coverage.'

Layer 6 is governance and continuous monitoring. Material debt decisions remain subject to the company's delegation of authority, treasury policy, risk appetite and board governance. The AI model is documented, validated and monitored for drift. Overrides are permitted but recorded. Realised cash flow, covenant outcomes and refinancing events are fed back into the validation process. This closes the loop between prediction and actual performance and prevents the model from becoming a static technology implementation.

Proposed AI-enabled financial risk management framework for debt financing

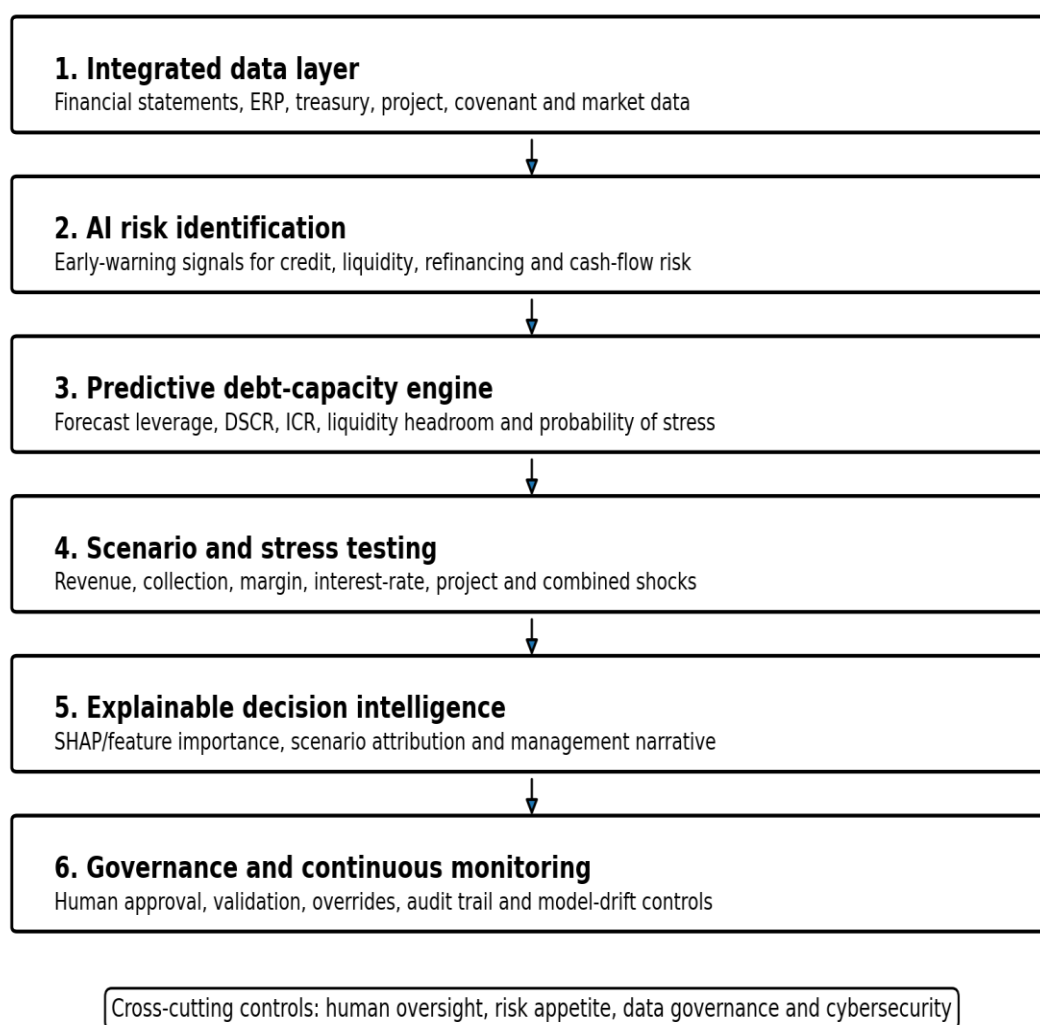


Figure 2: Proposed six-layer AI-enabled financial risk management framework for corporate debt financing. Source: Author conceptualisation based on the reviewed literature

Table 3: Framework layers, inputs, outputs and controls

Layer	Primary inputs	Analytics	Output	Core control
Data	ERP, treasury, project, market	Reconciliation/feature engineering	Controlled risk dataset	Data ownership and lineage
Risk identification	Financial + operating indicators	Rules, anomaly detection, ML	Early-warning alerts	Threshold governance
Debt capacity	Forecast drivers and debt schedule	Regression/classification/ensembles	Leverage, DSCR, ICR, risk probabilities	Benchmark and calibration
Stress testing	Management scenarios	Sensitivity and simulation	Downside cash and covenant headroom	Scenario approval
Explainability	Model output + feature effects	SHAP/feature importance	Ranked risk drivers and narrative	Independent challenge
Governance	All prior layers	Monitoring and workflow	Approval, override, escalation	Audit trail and model-drift review

9. Core Financial Metrics and Predictive Extensions

The framework deliberately preserves conventional financial metrics because they provide a transparent bridge between machine-learning predictions and corporate-finance decisions. Debt/EBITDA is expressed as total interest-bearing debt divided by EBITDA. ICR is commonly represented as EBIT or EBITDA divided by interest expense, depending on policy and covenant definition. DSCR can be represented as cash flow available for debt service divided by required principal and interest payments. Net debt equals gross interest-bearing debt less unrestricted cash and cash equivalents.

The AI extension is forward looking. Instead of reporting only that current DSCR is 1.8x, the system should estimate the expected DSCR distribution over the financing horizon, the probability of falling below a covenant threshold, the variables driving the downside and the sensitivity to management actions. A similar approach applies to leverage and liquidity headroom. The objective is not to create a single opaque 'AI score' but to connect predictions to multiple financially interpretable outcomes.

Forecast uncertainty should also be measured. An enterprise with a history of large forecast errors should not treat a base-case cash-flow forecast as equally reliable as an organisation with stable and accurate forecasting. Historical variance between forecast and actual cash generation can therefore be included as a model feature or used to widen the downside range. This is particularly relevant to FP&A functions because the quality of forecasting becomes an explicit component of debt risk.

A practical dashboard could display current metric, base forecast, downside forecast, probability of threshold breach, top three risk drivers and

recommended management actions. This format gives senior management a clear view of both level and direction of risk while retaining the underlying model for specialist review.

10. Scenario and Stress-Testing Architecture

Stress testing is the mechanism that converts prediction into financing resilience. The first scenario should be a revenue or volume shock. A 10-15% decline, for example, can be translated through margins, working capital and cash flow to show the effect on ICR and DSCR. The exact shock should be calibrated to the company's sector and historical volatility rather than adopted mechanically.

A second scenario should focus on collections. In project and service businesses, an increase in receivable days can produce a liquidity gap even when reported revenue is unchanged. The system should calculate additional working-capital funding, peak facility utilisation and the time required to recover liquidity. A third scenario should model interest rates. For floating debt, higher reference rates immediately affect debt service; for fixed debt, the shock should be applied at refinancing dates.

A fourth scenario should reflect project execution, such as cost overruns, delayed milestones or lower certified revenue. A fifth should combine multiple adverse conditions. Combined stresses are important because management actions that are sufficient under a single shock may be inadequate when shocks interact. AI can support this process by estimating nonlinear interactions, but scenario design should remain subject to finance and risk judgement.

The resulting output should be used to compare financing alternatives. Management can test whether a lower amount, longer maturity, different amortisation profile, interest-rate hedge, additional committed line or delayed capital expenditure

produces a more resilient structure. In this way, AI-enabled risk analysis becomes an instrument-design tool rather than merely a warning system.

11. Explainability and Human-in-the-Loop Governance

Explainability is essential because debt financing decisions affect liquidity, strategic flexibility, lender relationships and potentially the survival of the enterprise. Recent systematic reviews show that financial XAI commonly uses feature importance, SHAP, rule-based methods and related approaches to make complex models more understandable (Cerneviciene & Kabasinskas, 2024; Weber *et al.*, 2024). Yeo *et al.*, (2025) and Khan *et al.*, (2025) also emphasise that explainability is a central challenge in the deployment of advanced financial AI.

The proposed governance model has four levels. First, the model owner is responsible for data, methodology, documentation and change control. Second, an independent reviewer or model-risk function challenges assumptions, validation design and stability. Third, finance and treasury interpret the outputs within the commercial context. Fourth, the authorised executive committee or board approves material financing in accordance with delegated authority.

A model should never be allowed to approve debt autonomously. Qualitative considerations can materially change the decision: an acquisition may have strategic value not visible in historical data; a new government-backed contract may alter cash-flow risk; or a lender may provide terms that change refinancing exposure. Human judgement is therefore not a weakness in the framework; it is a required control layer.

Overrides should be formal rather than informal. If management accepts financing despite an elevated model risk, the decision record should state why, identify mitigating actions and define monitoring triggers. Conversely, management may reject financing even when the model indicates acceptable risk because of strategic or governance considerations. The audit trail makes the decision process transparent and supports subsequent learning.

12. Data Governance, Cybersecurity and Model Risk

AI quality cannot exceed data quality. Saudi corporate groups often operate multiple subsidiaries, ERP configurations and project systems, creating challenges in master-data consistency and account mapping. Before advanced analytics are introduced, the organisation should establish controlled data definitions, ownership, reconciliation rules and

access permissions. Sensitive debt and cash information should be protected through role-based access, encryption, secure environments and appropriate retention policies.

Model risk includes more than algorithmic error. It covers inappropriate variables, overfitting, data leakage, biased samples, unstable relationships and use outside the model's intended scope. Corporate-default events are relatively rare, which can create class-imbalance problems. Kuiziniene *et al.*, (2022) highlight imbalance and preprocessing as recurring issues in financial-distress research. Validation should therefore include precision, recall, F1 score, ROC-AUC, calibration and, where relevant, economic-cost measures rather than accuracy alone.

Out-of-time validation is particularly important. A model that performs well in a random train-test split may fail when economic conditions change. Olson *et al.*, (2021) emphasise model uncertainty and ongoing monitoring in corporate-debt loss modelling. The proposed framework accordingly requires drift monitoring, periodic recalibration and benchmarking against simpler baselines.

Generative AI creates additional risks if used to analyse contracts, board papers or narrative disclosures. Large language models can summarise text efficiently but may generate unsupported statements. Any extracted covenant, maturity or financial obligation should therefore be verified against the original document before it is used in a financing decision. Confidentiality should also be considered when selecting the technical environment.

13. Conceptual Propositions

The literature and framework support five propositions for future empirical testing.

Proposition 1: Integrating financial, operational and market data will provide earlier identification of debt-related risk than financial-statement ratios alone. The logic is that deterioration often begins in operational variables before it appears in periodic accounts.

Proposition 2: Machine-learning models will improve prediction of covenant stress and debt-service weakness when nonlinear relationships and interaction effects are material. This proposition is consistent with findings in corporate default research but requires Saudi-specific validation rather than direct transfer of foreign results.

Proposition 3: Explainable AI will increase managerial acceptance and effective use of predictive debt-risk models compared with black-box outputs of similar predictive accuracy. The proposition reflects

the governance needs of CFOs, boards, lenders and auditors.

Proposition 4: Scenario-based AI decision support will produce more resilient debt structures than single base-case analysis because it allows financing amount, tenor and amortisation to be optimised against downside conditions.

Proposition 5: The value of AI-enabled debt-risk systems will be positively associated with data-governance maturity and model-governance quality. Advanced algorithms cannot compensate for inconsistent data, weak controls or unrecorded management overrides.

14. Practical Implementation Roadmap for Saudi Enterprises

Implementation should begin with a finance problem rather than an AI tool. Phase 1 is diagnostic. The company maps debt facilities, covenant definitions, forecasting processes, data sources and historical stress events. It identifies where decisions are currently delayed or insufficiently forward looking. A pilot use case may focus on liquidity and covenant forecasting because these outputs are easily understood and directly linked to debt decisions.

Phase 2 establishes the data foundation. Finance, treasury, IT and risk agree on data owners,

definitions and reconciliation. Historical monthly data are assembled with enough depth to capture business cycles where possible. Data quality issues are documented rather than silently corrected.

Phase 3 develops benchmark models. A transparent logistic or scorecard model should be compared with tree-based methods such as random forest or gradient boosting. More complex models should only be retained if they provide stable incremental value. Explainability is designed at the same time as the model rather than added after deployment.

Phase 4 integrates scenario analysis and governance. The model is connected to the enterprise forecast, debt schedule and stress-testing templates. Approval thresholds, override rights, review frequency and escalation triggers are documented. Material changes are subject to change control.

Phase 5 moves to continuous monitoring of realised risks, management actions and model performance. The objective is an evolving finance capability rather than a one-time AI project, consistent with literature emphasising robust procedures and context-specific implementation (Tian *et al.*, 2024; Montevechi *et al.*, 2024).

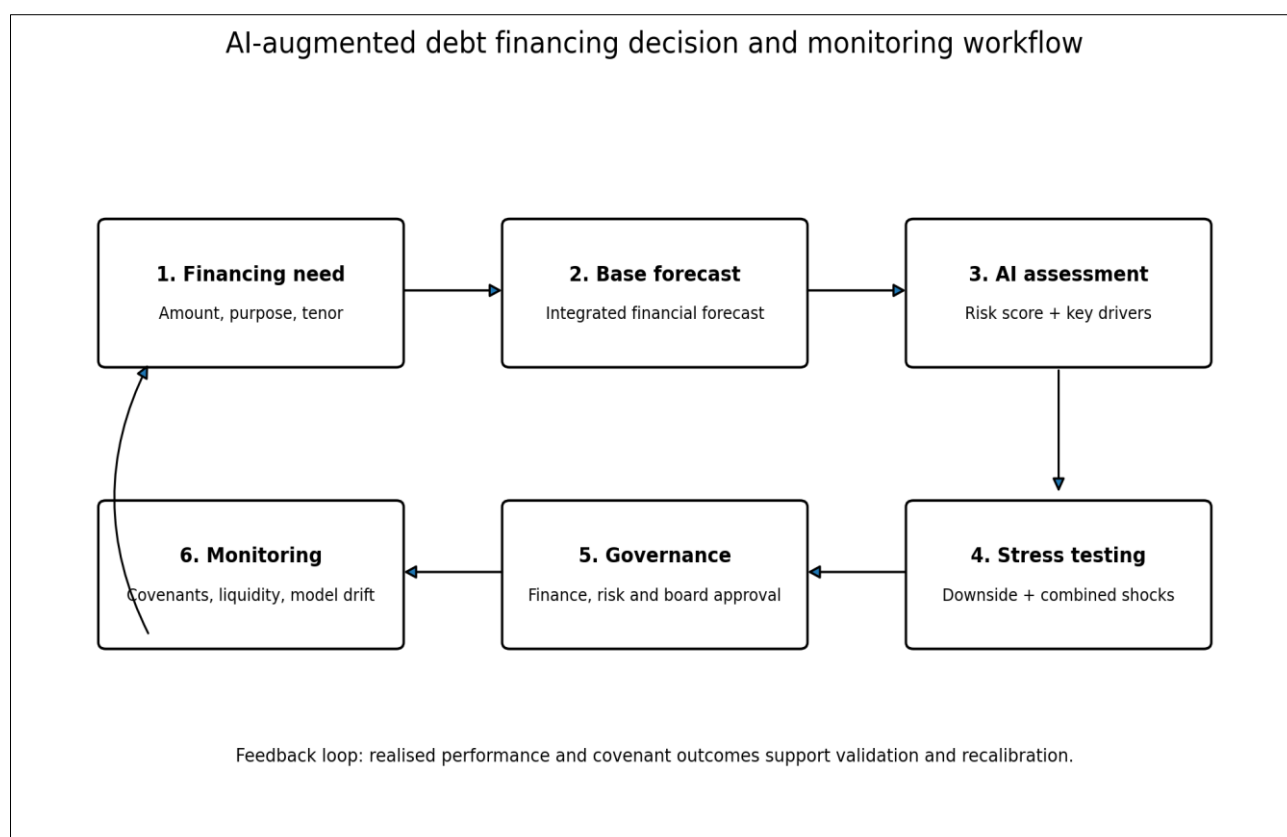


Figure 3: AI-augmented debt financing decision and monitoring workflow. Source: Author conceptualisation

Table 4: Suggested implementation KPIs for an enterprise pilot

Dimension	Example KPI	Purpose	Governance note
Forecasting	Cash-flow forecast error	Measures quality of the base input to debt analysis.	Review by FP&A monthly.
Liquidity	Minimum forecast liquidity headroom	Shows buffer under base and stress cases.	Threshold approved by treasury/risk.
Debt service	Probability of DSCR covenant breach	Creates forward-looking covenant warning.	Escalate above defined probability.
Model	Out-of-time ROC-AUC/calibration	Tests predictive stability.	Independent validation required.
Explainability	Share of material alerts with documented drivers	Ensures model output can be challenged.	No unexplained high-risk alert used for approval.
Governance	Override rate and realised outcome	Tests judgement quality and model limitations.	Every override requires rationale.

15. Managerial and Policy Implications

For CFOs, the framework turns debt financing into a continuous risk-management process by linking leverage, cash generation, stress exposure and explainable model warnings. For FP&A, forecast variance, cash conversion and project assumptions become direct inputs to debt-risk analysis; for treasury, the framework supports maturity planning, liquidity buffers and interest-rate management. Boards need not inspect algorithms, but should understand model purpose, limitations, key drivers and override conditions.

At the policy level, the framework complements Saudi debt-market development by focusing on issuer readiness. Market-development initiatives can broaden access to debt, but sustainable corporate issuance also requires reliable forecasting, transparency, credit assessment and governance. A stronger issuer-risk capability can therefore support the objectives of deeper and more diversified financing without implying that increased leverage is desirable in every case.

16. Research Gaps and Future Empirical Design

The most important research gap is the limited availability of Saudi enterprise-specific evidence on AI-supported corporate debt decisions. Much of the default-prediction literature uses North American, European or Asian datasets. Results from those environments should not be assumed to transfer directly to Saudi companies because accounting practices, financing structures, sector composition, ownership patterns, project exposure and lender relationships differ.

A future empirical study could assemble a panel of Saudi enterprises with monthly or quarterly data and define outcomes such as covenant stress, delinquency, rating deterioration or restructuring. Predictors could include leverage, DSCR, ICR, free cash flow, working-capital days, forecast error, project variance, maturity concentration and interest-rate exposure. Logistic regression should be

benchmarked against random forest, XGBoost and, where sample size permits, neural networks using out-of-time ROC-AUC, precision, recall, F1 score and calibration. Future streams should also examine sukuk-specific issuer risk, the effect of explainability on managerial acceptance, and verified text analytics for annual reports and covenant documents (Chen *et al.*, 2023).

These empirical extensions would convert the current conceptual framework into a validated Saudi decision model and could provide evidence relevant to lenders, issuers, regulators and researchers.

17. Limitations

The paper has four principal limitations. First, it is conceptual and does not estimate a new predictive model using Saudi company data. The framework therefore requires empirical validation before it can be treated as a production risk model. Second, the academic literature is heterogeneous; algorithms, samples, default definitions and performance metrics differ, limiting direct comparison. Third, the pace of AI development means that techniques and governance expectations will continue to evolve. Fourth, public information on corporate debt performance is less granular than the internal data that would be required for enterprise implementation.

These limitations do not invalidate the framework, but they define its appropriate use. It should be interpreted as a structured architecture for research and implementation, not as evidence that AI will automatically improve every debt decision or that a specific algorithm is optimal for all Saudi enterprises.

18. CONCLUSION

Saudi Arabia's financial transformation is expanding the strategic role of debt markets and corporate credit in supporting private-sector growth

and economic diversification. For enterprises, broader access to financing creates opportunity but also increases the need for disciplined management of leverage, liquidity, refinancing, interest-rate and project risks. Traditional finance tools remain essential, yet the growing volume and frequency of financial and operational data create a strong case for predictive analytics.

The evidence reviewed in this paper suggests that machine learning can improve the identification of complex risk patterns and corporate distress in appropriate settings. The strongest applications do not replace financial analysis; they augment it. The proposed six-layer framework therefore combines integrated data, AI-supported early warning, predictive debt-capacity analysis, scenario and stress testing, explainable decision intelligence, and governance with continuous monitoring.

The framework's central principle is that AI should support accountable human decision-making. Debt financing should not be approved by an autonomous model. Instead, model outputs should be interpreted by finance and risk professionals, tested against scenarios, explained in understandable terms and approved within established governance. The combination of predictive capability and transparent control is particularly important in a developing debt-market environment where companies may gain access to a wider range of instruments and maturities.

For Saudi enterprises, the practical opportunity is to connect FP&A, treasury, risk management and digital transformation into a single debt-decision capability. A mature system would not merely answer whether a company can borrow today. It would estimate how much debt is sustainable, identify the conditions under which that conclusion changes, explain the drivers, compare alternative structures and monitor risk after financing is executed. Future research should test these propositions using Saudi corporate data and evaluate whether AI-enabled early-warning systems predict covenant or liquidity stress earlier than conventional approaches. Such evidence would provide a stronger foundation for responsible AI adoption in corporate finance under Vision 2030.

REFERENCES

- Alam, N., Gao, J., & Jones, S. (2021). Corporate failure prediction: An evaluation of deep learning vs discrete hazard models. *Journal of International Financial Markets, Institutions and Money*, 75, 101455. <https://doi.org/10.1016/j.intfin.2021.101455>
- Boukhatem, J. (2022). How does financial risk affect sukuk market development? Empirical evidence from ARDL approach. *Heliyon*, 8(5), e09453. <https://doi.org/10.1016/j.heliyon.2022.e09453>
- Bussmann, N., Giudici, P., Marinelli, D., & Papenbrock, J. (2021). Explainable machine learning in credit risk management. *Computational Economics*, 57, 203-216. <https://doi.org/10.1007/s10614-020-10042-0>
- Capital Market Authority. (2024). Strategic Directions to Develop Sukuk and Debt Capital Market. Riyadh, Saudi Arabia.
- Carmona, P., Dwekat, A., & Mardawi, Z. (2022). No more black boxes! Explaining the predictions of a machine learning XGBoost classifier algorithm in business failure. *Research in International Business and Finance*, 61, 101649. <https://doi.org/10.1016/j.ribaf.2022.101649>
- Cernevičienė, J., & Kabasinskas, A. (2024). Explainable artificial intelligence (XAI) in finance: A systematic literature review. *Artificial Intelligence Review*, 57, 216. <https://doi.org/10.1007/s10462-024-10854-8>
- Chen, T.-K., Liao, H.-H., Chen, G.-D., Kang, W.-H., & Lin, Y.-C. (2023). Bankruptcy prediction using machine learning models with the text-based communicative value of annual reports. *Expert Systems with Applications*, 233, 120714. <https://doi.org/10.1016/j.eswa.2023.120714>
- Financial Sector Development Program. (2025). Annual Report 2024. Saudi Vision 2030.
- International Monetary Fund. (2024). Saudi Arabia: Financial Sector Assessment Program- Financial System Stability Assessment. IMF Staff Country Report No. 2024/281. <https://doi.org/10.5089/9798400288074.002>
- Khan, F. S., Mazhar, S. S., Mazhar, K., AlSaleh, D. A., et al. (2025). Model-agnostic explainable artificial intelligence methods in finance: A systematic review, recent developments, limitations, challenges and future directions. *Artificial Intelligence Review*, 58, 232. <https://doi.org/10.1007/s10462-025-11215-9>
- Kuiziniene, D., Krilavicius, T., Damasevicius, R., & Maskeliunas, R. (2022). Systematic review of financial distress identification using artificial intelligence methods. *Applied Artificial Intelligence*, 36(1), 2138124. <https://doi.org/10.1080/08839514.2022.2138124>
- Matyori, E. A. (2025). The financial sector in the Kingdom of Saudi Arabia's Vision 2030: Evaluation and achievements. *Journal of Economic, Administrative and Legal Sciences*, 9(1), 87-102. <https://doi.org/10.26389/AJSRP.E040724>

- Montevechi, A. A., Miranda, R. C., Medeiros, A. L., & Montevechi, J. A. B. (2024). Advancing credit risk modelling with machine learning: A comprehensive review of the state-of-the-art. *Engineering Applications of Artificial Intelligence*, 137, 109082. <https://doi.org/10.1016/j.engappai.2024.109082>
- Moscatelli, M., Parlapiano, F., Narizzano, S., & Viggiano, G. (2020). Corporate default forecasting with machine learning. *Expert Systems with Applications*, 161, 113567. <https://doi.org/10.1016/j.eswa.2020.113567>
- Nallakuruppan, M. K., Balasubramanian, B., Balusamy, B., Shri, M. L., Malathi, V., Veeraraghavan, M., & Bhattacharyya, S. (2024). An explainable AI framework for credit evaluation and analysis. *Applied Soft Computing*, 153, 111307. <https://doi.org/10.1016/j.asoc.2024.111307>
- Olson, L. M., Qi, M., Zhang, X., & Zhao, X. (2021). Machine learning loss given default for corporate debt. *Journal of Empirical Finance*, 64, 144-159. <https://doi.org/10.1016/j.jempfin.2021.08.009>
- Perboli, G., & Arabnezhad, E. (2021). A machine learning-based DSS for mid and long-term company crisis prediction. *Expert Systems with Applications*, 174, 114758. <https://doi.org/10.1016/j.eswa.2021.114758>
- Saudi Central Bank. (2024). Financial Stability Report 2024. Riyadh, Saudi Arabia.
- Sigrist, F., & Leuenberger, N. (2023). Machine learning for corporate default risk: Multi-period prediction, frailty correlation, loan portfolios, and tail probabilities. *European Journal of Operational Research*, 305(3), 1390-1406. <https://doi.org/10.1016/j.ejor.2022.06.035>
- Theodorakopoulos, L., Theodoropoulou, A., & Bakalis, A. (2025). Big data in financial risk management: Evidence, advances, and open questions: A systematic review. *Frontiers in Artificial Intelligence*, 8, 1658375. <https://doi.org/10.3389/frai.2025.1658375>
- Tian, X., Tian, Z., Khatib, S. F. A., & Wang, Y. (2024). Machine learning in internet financial risk management: A systematic literature review. *PLOS ONE*, 19(4), e0300195. <https://doi.org/10.1371/journal.pone.0300195>
- Weber, P., Carl, K. V., & Hinz, O. (2024). Applications of explainable artificial intelligence in finance: A systematic review of finance, information systems, and computer science literature. *Management Review Quarterly*, 74, 867-907. <https://doi.org/10.1007/s11301-023-00320-0>
- Yeo, W. J., Van Der Heever, W., Mao, R., Cambria, E., Satapathy, R., & Mengaldo, G. (2025). A comprehensive review on financial explainable AI. *Artificial Intelligence Review*, 58, 189. <https://doi.org/10.1007/s10462-024-11077-7>