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Original Research Article

AI-Based Risk Governance and Credit Decision Systems in Saudi Financial Institutions under Vision 2030

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Abstract: AI has become one of the most influential factors in evaluating credit risk and detecting frauds in credit portfolios. Nevertheless, there is still an urgent need to consider ethical aspects related to incorporating AI into loan decision-making processes especially concerning the Saudi financial sector amid its ongoing transition according to the Vision 2030. In this review paper, I explore how an AI risk management governance system and a credit decision framework can lead to enhanced credit decision making, responsible financial inclusion and institutional stability. Rather than limiting myself to analyzing algorithmic precision, I perform an extensive narrative review covering different phases of credit decision-making process: from the sourcing and preparation of relevant data to model construction, explanations, manual supervision, fairness assessment, regulatory compliance, portfolio monitoring and auditing assurance. For that purpose, I employ a systematic narrative review methodology and utilize academic articles and other materials published within the time period from 2020 to 2025. As a result of reviewing relevant literature, I found that AI could improve credit decisions through detecting non-linear risk relationships, refining early warning signals, conducting automated document analysis and segmenting borrowers in greater detail. Yet such improvements would be possible only in case companies ensure proper data handling, model management, mitigation of biases, cyber risks, outsourcing issues and Shariah compliance. Therefore, I propose an AI Credit Governance Framework consisting of five layers.

Keywords: Artificial Intelligence, Credit Risk, Risk Governance, Saudi Financial Institutions, Vision 2030, Explainable AI, Banking, Fintech, Responsible Finance.

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1. INTRODUCTION

The Saudi financial sector is evolving in an era of increasing digitalization, fintech competition, open banking trends, cashless payments and regulatory reform. Through Vision 2030, the government seeks to harness the financial sector to fuel private-sector growth, diversification of investments and financial inclusion. As a result, credit decision frameworks are not just internal bank processes. Instead, they help ensure households' access to finance, expansion of small businesses, resilience of the national financial institutions and trust in the financial system. AI can contribute significantly to credit decision-making as it helps manage vast amounts of transactional, behavioural, macro-economic and alternative datasets much quicker than manual underwriting does. Besides, there are risk factors that may not be visible in traditional scorecards, particularly when the borrower's behaviour is changing rapidly following a shock, market volatility or industry transformation. However, recent guidance on credit decisions in the financial sector warns about increased opacity, data dependency, vendor concentration and complex governance in AI systems (Financial Stability Board, 2024; Basel Committee on Banking Supervision, 2024).

In the traditional credit decision governance, responsibility is divided among business origination, credit risk, compliance, internal audit, information security and senior management teams. These roles are disrupted in AI models as the model output may have a decisive effect even before the decision-maker comprehensively understands the reasons for recommending it. There might be technically perfect models but they will not work for reasons like instability of input data, biases, lack of explanations for decisions made or difficulties in monitoring the model in post-deployment phase. Moreover, this problem is more urgent in credit risk assessment as it involves customers and money allocations. Finally, the topic at hand is linked to data protection, principles of responsible AI, SAMA expectations, PDP Act and Vision 2030 financial inclusion objectives (SDAIA, 2023; SAMA, 2022; Vision 2030, 2024). Therefore, it is essential to look at AI credit decision frameworks through the perspective of governance.

2. Motivation and Research Gap

The inspiration for the review stems from a clear disconnect between fast-paced AI adoption and lagging development of governance processes in banks and finance companies. While many financial institutions are currently employing AI for fraud detection, collections prioritization, customer segmentation and credit scoring, their degree of implementation maturity varies widely. On the one hand, academic research proves the efficacy of machine learning in improving prediction accuracy in credit risk scenarios. On the other hand, literature consistently highlights explainability, model fairness and risk management concerns as obstacles for model implementation (Bussmann *et al.*, 2021; Mashrur *et al.*, 2020; Arrieta *et al.*, 2020). Besides, global supervisory guidance adds the risk of creating concentration effects as all the financial institutions in a country may use the same cloud providers, datasets or AI models (FSB, 2024; OECD, 2024).

Saudi-specific literature is still being formed. While there are numerous papers that talk about growth of fintechs in Saudi Arabia, digital transformation in the banking sector or financial modernization overall, there are far fewer research pieces that incorporate the credit risk governance, AI assurance and Vision 2030 considerations in one framework. This paper fills this gap by exploring how the implementation of AI could contribute to better credit decisions.

3. Aim, Objectives and Research Questions

The aim of the review is to establish a governance perspective on AI-driven credit decision systems in Saudi Arabia. In contrast with prior studies testing an individual credit scoring algorithm, this review aims to evaluate AI governance throughout the credit decision process to align its aspects of prediction, approval, monitoring and responsibility.

The objectives of the review include identification of AI approaches to credit risk management and credit decision making between 2020 and 2025; evaluation of governance risks related to the use of AI, including but not limited to issues of explainability, privacy, potential biases, model drift, increased cybersecurity threats and dependence on third parties; analysis of the above risks' connection with digital transformation in the Saudi financial sector, including development of fintech solutions, SME financing, Open Banking initiatives and responsible use of data; development of review-based AI governance framework for credit decisions in the region.

The research questions that will drive the review include the following:

RQ1: Which capabilities of AI are relevant to credit decisions in the Saudi financial sector?
RQ2: What governance controls are needed to translate AI predictions into responsible credit decisions?
RQ3: How can AI-enabled credit decision systems advance Saudi Vision 2030 goals without jeopardizing fairness, accountability and stability?

4. REVIEW METHODOLOGY

A structured narrative review approach will be adopted. This methodology seems to be well-suited to a research object that is characterized by the involvement of several aspects – technological, normative, regulatory and contextual. The review process is based on the logic implied in the attached Springer's model, i.e., addressing a contemporary problem, identifying research questions, comparison of topics and finishing with a practice-oriented framework. The search included peer-reviewed journal articles, reports by authorities and other documents published between 2020 and 2025. Only those papers that mentioned any AI in credit risk, finance and general governance, explainable AI, banking model risk, financial-sector digitalization and Saudi Vision 2030 were included. Since the study relies on literature review methodology and not an empirical investigation, its results must be interpreted as the synthesized evidence, not as measurements made in Saudi financial institutions.

The inclusion criteria of sources relied on three steps. At first, sources' topicality with respect to AI credit capability, credit decision or financial sector governance was checked. Secondly, recency and institutional prestige (priority was given to sources indexed in Scopus, international standard setters and Saudi regulatory agencies) were evaluated. Finally, the information provided by the source was categorized under five headings – AI capability, governance risk, customers, regulatory compliance and Saudi Vision 2030 benefit. This methodology seems to be adequate since the topic demands an interdisciplinary approach – only such an approach could combine issues of AI with governance and regulation (NIST, 2023; ISO/IEC, 2023).

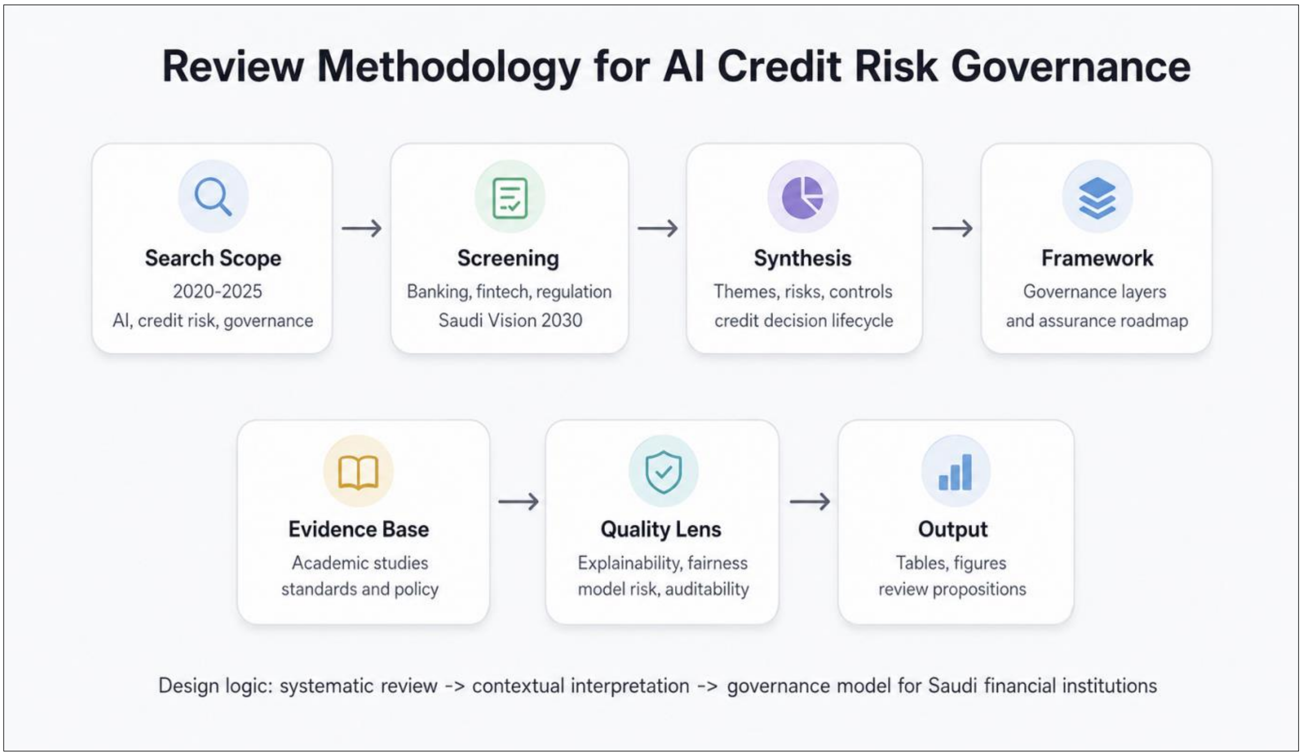

Figure 1: Review methodology and synthesis design for AI-based credit risk governance

5. AI Functions in Credit Decisions Systems

AI can be used to support credit decisions by using supervised learning methods, which include gradient boosting, random forest and artificial neural networks, to compute the borrower's default probability based on non-linear relationships between income, repayment history, payment behavior, exposure to industries and macro-economic factors. Text analytics is used to process unstructured information like bank statements, credit memoranda, client communication and financial notes. Anomaly detection can be employed to support fraud management as well as early warning signs of deviations in accounts or repayments. The use of generative AI can potentially increase efficiency of credit analysts' work through summarization of the documentation, although AI alone should not make the lending decision due to the risks of hallucination, confidentiality and lack of explainability (FSB, 2024; NIST, 2023).

The main benefit of using AI is not speed but better risk differentiation. Traditionally, credit scorecards tend to put the applicants into wide bands while AI is capable of recognizing unique combinations of features indicating change of risks. For example, in case of SME lending, AI can help lenders evaluate cash flow behaviors of the borrowers and decrease dependence on collateral. In the retail finance segment, it can facilitate affordability evaluation as well as prioritize collections. In case of Islamic banking, models can assist in the risk recognition while the product structures and customer management practices will remain aligned with the Shariah requirements. However, increased prediction accuracy does not mean better governance because it is important to provide the reasons for decisions, maintain proper documentation and treat clients fairly, particularly in case of rejections, changes in pricing or limits (Bussmann *et al.*, 2021; EBA, 2020).

6. Governance Risks and Controls

In AI-based credit decisioning systems, risks arise in ways that are different from those related to traditional credit models. Data risks occur in case the input data is inadequate, out-of-date, bias, unauthorized or poorly connected to the individual borrower. Model risks emerge in case of overfitting of the training set or failure in conditions of changed economics. Fairness risk can occur if protected or sensitive characteristics are present in the dataset implicitly through proxies like geographic location, occupation or payment pattern. Explainability risk is relevant to the loan-making process because all stakeholders, including clients, auditors and regulators need explanations for the decision. Operational risk includes cloud vulnerability, cyber threats, poor access control and deficient incident response. Outsourcing risk exists when a third-party algorithm is used by an institution without transparency or audit rights (OECD, 2024; FSB, 2024; Basel Committee, 2024).

To address the above risks effectively, it is necessary to implement controls at the three stages. Prior to implementation of the model, the organization needs to establish purpose, allowed datasets, prohibited features, validation criteria and owner responsibilities. During its usage, credit committee should specify whether AI results are advisory or if human intervention is required as well as prohibit automated processing in certain cases. Once implemented, internal audit and model risk teams need to monitor drift, overrides, adverse events, complaints and stress testing results. These controls align with the broader concept of trustworthy AI which requires reliability, validity, fairness, transparency, privacy and accountability in the entire lifecycle of the development (SDAIA, 2023; NIST, 2023; ISO/IEC, 2023).

7. Saudi Vision 2030 Context

The Saudi context adds a strategic element to the governance of AI credits. The objectives of Vision 2030 and the Financial Sector Development Program include building a stable, innovative and effective financial sector capable of promoting private-sector development. While digital banking and fintech will improve the reach of financial services, automation mismanagement will cause issues of trust if borrowers view decisions as opaque or biased. Thus, Saudi organizations need to manage their innovation with prudence. The Financial Sector Development Program stresses efficient financial institutions, inclusive finance, fintech development and advanced capital markets. By helping meet these goals, AI credit systems can improve SME credit access, cut down the manual processing time, detect negative changes in account health sooner and offer personalized products (Vision 2030, 2024; Ministry of Finance, 2023).

The data governance practices in Saudi Arabia are also worth considering. The Personal Data Protection Law, SDAIA AI Ethics Principles and SAMA programs related to digital finance imply that the AI implementation should ensure the security, privacy, accountability and transparency of data flows. Open banking will yield more credit data, yet there will also be an increased need for data sharing controls and consent management. Therefore, the governance of AI applications for credit should be tied to enterprise risk management, cyber risk management, compliance and Shariah governance, when it comes to Islamic financial products. In such an environment, the best credit AI systems will not be the most automated systems; they will be the most explainable, controllable and institutionally trustworthy systems.

8. Synthesis of Credit Use Cases and Assurance Mechanisms

Five credit use cases were identified in which AI would have particularly high relevance for Saudi financial institutions. They are as follows: application screening, probability-of-default estimation, affordability and vulnerability assessment, early warning monitoring and fraud and identity risk detection. While all use cases relate to credit, they affect customers in different ways, and governance needs to be tailored accordingly. For example, the model used for internal review and subsequent manual decision-making does not necessarily require stringent control measures. In contrast, a completely automated approval or rejection process calls for thorough and continuous testing.

The type of assurance also varies depending on the specific use case. For application screening, there should be controls for the verification of data sources and customer identity. Default prediction will require back-testing, calibration and monitoring of stability. Fairness review and outcome assessment should accompany affordability models. Early warning systems call for well-defined response protocols because alerts will need to turn into meaningful actions, instead of being another piece of unnecessary information on dashboards. Fraud models demand high levels of operational resilience and cybersecurity due to risks related to cyberattacks. In all cases, however, explainability must be explained in business terms. Credit officers cannot simply see mathematical formulas; they must see how the behaviors or financial characteristics of a borrower led to the risk classification.

9. Implementation Issues Facing Saudi Financial Institutions

The implementation issues facing Saudi financial institutions will most likely be practical, not theoretical. Top management might agree with AI principles, but the actual progress could be hindered by fragmentation of data, lack of completeness or consistency of legacy data fields, and outdated policies embedded into the historical data. This will cause problems because Saudi Arabia has a rapidly evolving economy with new sectors, freelancing, online business, and new ways for SMEs to operate. New industries, job roles and operating models have nothing to do with traditional lenders and, thus, should be re-approached with a new policy. In order to achieve this, AI credit governance should incorporate data refresh, human judgment and policy update.

Another potential issue is capability. AI credit governance requires knowledge of banking regulation, data analysis, cybersecurity, data science and risk appetite. These skills usually reside within different departments. As such, the best solution would be to establish a multidisciplinary committee along with appropriate escalation pathways. Vendor management is yet another issue since most organizations tend to use external AI platforms or collaborate with fintechs. Nevertheless, outsourcing will not shift responsibility. Therefore, agreements should explicitly state requirements regarding model documentation, data residency, audit, incident reporting, availability and exit strategy. Last but not least, the culture of an institution matters. Credit officers might reject AI as a tool, considering it detrimental to professional judgment, while data scientists could underestimate regulatory requirements. Thus, successful organizations would emphasize governance as a key aspect of any AI deployment.

10. Recurrent Themes Identified in the Literature

Four recurrent themes can be identified within the analyzed literature. The first of these is explainability as a criterion of legitimacy. In AI credit risk management, explanations are mandatory since there are legal, financial and reputational stakes involved. Explainability needs to be adjusted according to the type of stakeholder. Data scientists will want detailed feature contribution, credit officers will want to understand the business logic, auditors will want to validate results, and customers will want information about their case. Fairness is the second recurring theme since the question of ethics in AI remains vague. Organizations should conduct tests for potential disparities between model output across various customer groups. They should be documented along with the justification of any difference found, based on credit risk assessment rather than data bias. The third theme is resilience, meaning AI credit system robustness to economic environment, customer behavior and digital channel attacks. The last theme is accountability. A proper governance model needs to address who is authorized to deploy the system, what deviations from expected performance need human approval, and who is responsible for oversight.

As can be seen, governance of AI requires much more than data scientists' efforts. In addition to this, the board needs to approve a risk appetite, there needs to be a model inventory, validation procedure, documentation and escalation mechanism. Guidelines of international bodies such as NIST, ISO, the FSB and the OECD all converge toward a life-cycle governance model for trustworthy AI. The same life-cycle model can be adopted in Saudi Arabia in alignment with the national legislation, SAMA standards and Vision 2030 financial sector objectives. This way, the literature suggests implementing a hybrid approach in Saudi organizations, characterized by centralized standards for high-risk cases and business-unit responsibility for others.

11. Quality Criteria of the Scopus Review Paper

A good review paper should do more than simply cite existing papers. The first thing it must do is make an argument about the evidence presented and establish its unique contribution to knowledge. For this paper, it is the integration of AI credit scoring literature with the themes of risk management, financial governance and transformation of Saudi Arabia. The paper employs temporal boundaries, which run from 2020 to 2025. This choice was driven by the fact that during these years there was the acceleration of explainable AI models, open banking and digital finance beyond the pandemic period, as well as generative AI. Furthermore, this timeframe coincides with Saudi Arabian regulatory developments in the area of AI ethics and data protection. Other aspects of quality are concept clarity, topic relevance, clear methodology, credible references and practical importance. All of these elements are inherent in review papers by Springer, Elsevier and Emerald.

There is one important element of contribution made by this paper that is relevant not only to the AI literature but also credit scoring and governance. While numerous papers evaluate whether a model predicts default, they fail to ask the question of what process allows the prediction to turn into a defensible decision from both legal and institutional standpoints. This aspect is crucial since there are several other factors to consider. Credit products require not only the technical aspect, i.e. the model itself, but also people, policies, customer engagement, and product positioning. Some models can be inaccurate, while others – accurate but unsuitable for implementation due to lack of explainability, monitoring ability and defensibility against challenges. At the same time, some situations require more interpretability and hence simpler models due to higher customer impact. Hence, we suggest a risk-based philosophy to design AI solutions in Saudi Arabia.

12. Proposed Saudi AI Credit Governance Framework

Building upon the literature review, a five-layer Saudi AI Credit Governance Framework is proposed by this paper. The first layer is data and compliance foundation. It calls for legal data sourcing, customer consent, data minimization, data quality check, lineage record and secured storage. The second layer is model development and validation. It includes feature selection, model benchmarking, explainability assessment, stress test and independent validation. The third layer is explainable decision governance. It identifies human oversight threshold, human overrides, adverse action justification, Shariah review trigger and credit committee accountabilities. The fourth layer is portfolio risk assurance. It covers default trends, sector concentration, model drift, fairness indicator, cyber incidents and customer complaints monitoring. The fifth layer is Vision 2030 value realization. It assesses AI's impact in fostering responsible financial inclusion, SMEs lending, operational efficiencies, profitability, and market confidence.

The proposed framework should be cyclical instead of being a one-off process for approvals. Decision output from AI must be reviewed for further model enhancement, while customers' complaints and audit findings can help improve governance design. Good performance at one time does not guarantee future success as changing interest rates, employment conditions, government policy, inflation levels, and sector demands can cause model failure. Therefore, a model lifecycle management regime must be enforced to ensure the longevity of a model. The proposed AI Credit Governance Framework needs to define roles clearly. Credit decision belongs to business unit, model governance to risk management, compliance with regulation belongs to compliance, infrastructure security is the responsibility of technology department, and board takes care of risk appetite and accountability. Otherwise, an AI decision will become an orphaned item among data science, business and compliance groups.

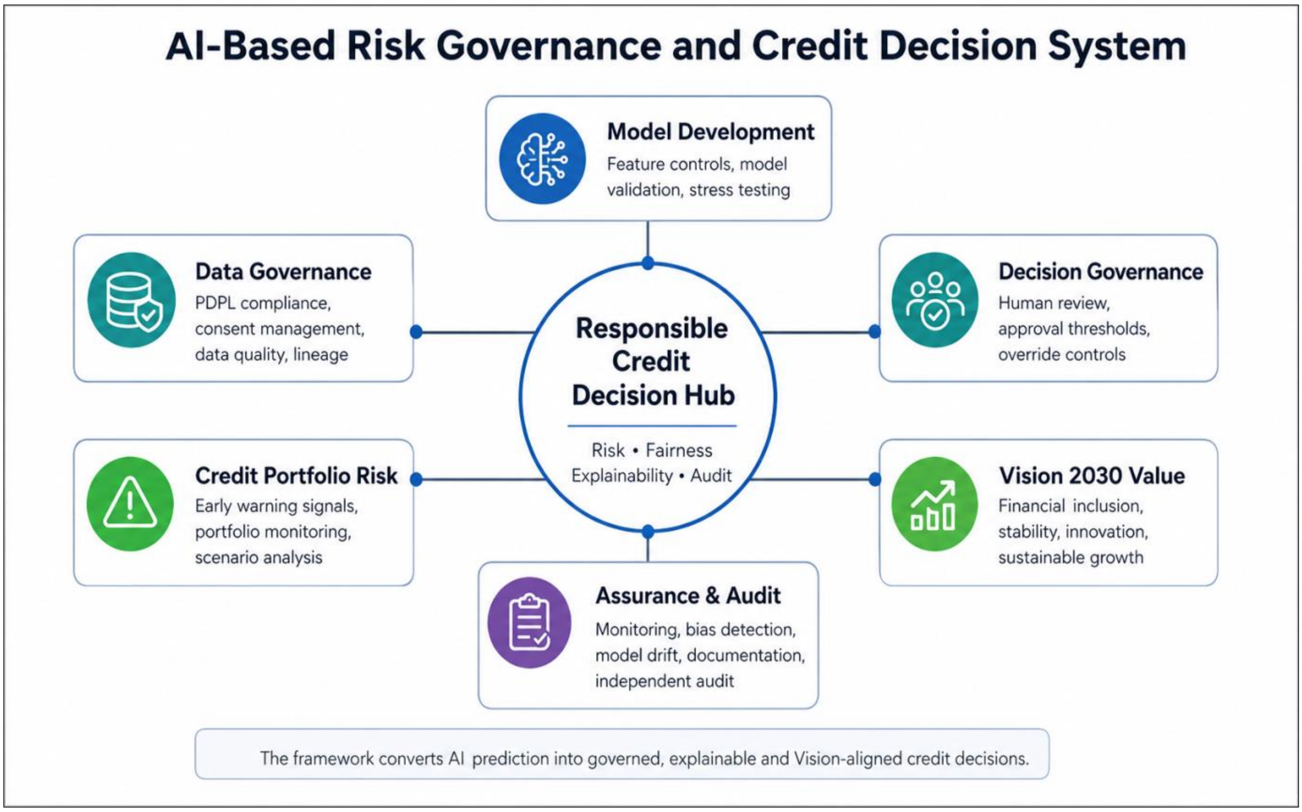

Figure 2: Integrated AI-based risk governance and credit decision framework for Saudi financial institutions

13. Review Propositions

Four propositions emerge from the literature synthesis that may serve as a guide for future empirical research efforts in the area of Saudi Arabia's Vision 2030 implementation. The first proposition is that AI credit models increase the quality of credit decision-making when the level of data governance maturity is high. Poor data lineage, lack of consent management and inconsistent income information or alternative sources will affect data reliability even if the algorithm itself is advanced. The second proposition is that explainability increases trust within institutions if the explanation links to credit policy rather than being presented as a technical chart. The third proposition is that human review of credit decision output is beneficial if the reviewer is empowered with questioning and overriding capabilities rather than merely being a passive human-in-the-loop. The fourth proposition is that the value of Vision 2030 will be realised when the use of AI in credit decision systems ensures responsible access to finance without portfolio risks. The propositions turn the results of this review into a Saudi research agenda in AI credit decision systems.

Each of the propositions offers a practical diagnostic tool. For example, does your organisation know which AI models have an effect on credit outcomes? Are the data sources lawful, relevant and current? Can your team explain the decision in plain language? Is model override documented? Are fairness metrics monitored on the portfolio level? Do you audit third-party suppliers? Are Shariah and customer protection considerations included where applicable? All these diagnostic questions will contribute to implementing AI governance from general concept into a tangible process. This, in turn, will help in conducting audits and supervisory reviews.

Table 1: Review questions, evidence focus and expected contribution

Research question	Evidence focus	Governance lens	Expected contribution
RQ1	AI models for credit scoring, fraud alerts and early warning	Capability and suitability	Identifies useful AI functions for Saudi credit markets
RQ2	Explain ability, bias, data privacy, model drift and vendor dependency	Risk control and accountability	Defines controls needed before and after deployment
RQ3	Vision 2030, FSDP, open banking and responsible finance	Strategic alignment	Links AI credit governance to national transformation

Table 2: Governance controls for AI-based credit decision systems

Governance area	Key risk	Required control	Saudi relevance
Data governance	Unlawful, biased or low-quality data	Consent, lineage, minimization, quality checks	PDPL, open banking and customer trust
Model governance	Overfitting, drift and opacity	Independent validation, stress tests, explainability	SAMA-aligned risk management and audit
Decision governance	Unfair approvals, declines or pricing	Human review, override logs, adverse-decision reasons	Financial inclusion and responsible lending
Operational assurance	Cyber, cloud and vendor concentration	Access controls, vendor audit rights, incident response	Financial stability and system resilience
Portfolio monitoring	Hidden concentration and delayed deterioration	Early warning dashboards and fairness monitoring	SME finance and Vision 2030 value

14. DISCUSSION

The review confirms that using AI to support judgement is more beneficial for financial decision making than relying on AI as a means of replacing traditional governance. While in Saudi financial organisations, artificial intelligence makes credit risk analysis more accurate and faster, it requires being used in the context of accountable processes. The bank cannot defend its lending decision based only on its statement that the model recommended this decision. Instead, it needs to demonstrate what data it used, why the model was chosen, what bias analysis was performed, whose approval the logic of the decision had, how a customer may contact the lender about the decision, and how long-term performance of the client is monitored. These requirements fit the globally recognised approach and are aligned with Vision 2030's principles of responsible AI usage in the Saudi financial sector.

Moreover, this review demonstrates that AI credit decision governance is different depending on the type of use case involved. Marketing decisions can be taken using less rigorous controls than automated decisions in credit applications. Prioritising debt recovery processes based on predictive analytics also involves fewer issues than pricing models. Risk-tiering allows avoiding unnecessary bureaucracy while applying strict control to critical decisions. This will support further innovation as it gives fintech teams the freedom to experiment, ensuring safety for clients and the organisation. Moreover, Scopus and Web of Science style requirement of linking conceptual synthesis to proposed frameworks, implications and research directions is fulfilled.

15. Recommendations

Saudi financial institutions should first establish AI credit governance policies, which will be endorsed at the board level or the executive risk committee. The policies should outline key areas, including definition of use cases, requirement for validation, data protection principles, need for explainability, obligation and right to audit vendors, etc. The institutions should form multidisciplinary review teams comprising credit risk, data science, compliance, cybersecurity, legal, customer experience, and internal audit. The reason for multidisciplinary is that the AI credit decisions will impact various risk categories.

Second, the institutions should ensure explain ability by design, whereby model developers do not add explanations after the deployment process, but rather choose modelling techniques whose outputs can be used to make explanations for the purposes of credit officers, customers, and regulators. Third, model performance assessment will go beyond accuracy. The institutions will monitor calibration, stability, rate of false positives, rate of false negatives, adverse impact, override rates, customer complaints, collections results, and portfolios concentration. Fourth, Saudi banks and fintech lenders must ensure their local capacity building in terms of AI validation and audit, model risk management, data governance, and responsible digital finance. The fifth recommendation would entail industry-wide and regulators' collaboration on providing guidance on documentation of models, AI testing for fairness, and audit evidence in relation to AI credit decisions.

16. Limitations and Future Research

The limitations of the literature review stem from the fact that very little has been documented on operational aspects of the AI credit decisions made in the country. The lack of documentation means that there is no detailed information about what happens in the processes that are kept confidential. In addition, another limitation concerns the rapid developments in the world of artificial intelligence. Therefore, new generative AI techniques, synthetic data generation technologies, and real-time underwriting platforms may render any governance principles redundant soon enough. For these reasons, the review has provided a structured analysis. The future research can focus on applying the governance framework in a case study involving Saudi banks, finance companies, and fintech lenders. Empirical studies can investigate the maturity of model governance in different institutions, the attitudes of customers towards such decisions, outcomes in terms of fairness to SMEs, as well as the relationship between explain ability and credit officers' trust.

17. Implications for Stakeholders

The review implies a number of implications for different stakeholders. First of all, it is related to the importance of aligning the process of AI credit governance with risk appetite and the level of board oversight. It does not mean that directors have to evaluate every technical parameter of a model. At the same time, there is a requirement for directors to receive proof of inventory, validation, monitoring, and challenge of the high-impact models.

For executive management, the implication is that AI has to be used as an enterprise capability, not just an experiment. Decisions on investing in the technology should cover such areas as hiring relevant staff, building data infrastructure, establishing the governance processes, and communicating with customers about automation in decisions.

For chief risk officers, it implies the integration of AI models with credit risks and model risks within the existing frameworks. Acceptable model types, validation thresholds, approval of dashboards, and approval of overriding patterns have to be defined in advance.

Legal and compliance departments imply that the design of data protection, explain ability of results, and treatment of customers has to be performed in advance, not as soon as any complaints arise, or audit or supervisory findings occur.

Internal auditors can now review such documents as model documentation, data lineage, access controls, agreements with vendors, evidence of human review, and results of post-deployment monitoring.

For fintech partners, the implication is that innovation in terms of speed or cost reduction has to be justified through providing evidence. It means that a fintech model has to provide documentation, explain ability solutions, testing for bias, and secure implementation.

Customers, of course, want to receive faster and more inclusive credit services while understanding how the decision was made and why it had a negative impact. Saudi financial institutions need to provide such explanations to their customers by notifying them in case when an automated analysis influenced decisions, mentioning factors which resulted in the negative decision, allowing corrections and reconsideration.

18. CONCLUSION

AI-enabled credit decision making systems have the potential to be the major catalysts of transformation of the Saudi financial sector as long as they will be managed with discipline. Based on the review conducted in this work, AI has a great capacity to enhance risk management, fraud detection, documentation analysis and portfolio monitoring.

However, such systems are able to bring a number of ethical, legal and business risks, including opacity, data manipulation and discrimination, if there is no adequate governance in place. Therefore, the crucial question for Saudi financial companies following Vision 2030 is not whether to use AI at all, but how to govern, explain and align AI systems with the strategic goals of the state. The suggested governance framework can serve as a practical roadmap from data governance to modelling, explain ability, monitoring and Vision 2030.

The last contribution of this paper was made intentionally practical in order to satisfy the need of Saudi financial companies for an AI governance model that can be understood by their risk and audit committees, monitored by the supervision, trusted by their customers, and constantly improved by their data management teams. Responsible automation is based upon transparency, feedback and accountability. Future empirical studies may develop metrics for measuring AI maturity of companies' credit management systems. Field studies can focus on understanding how Saudi customers perceive automated decisions, how analysts analyze explanations provided by automated systems, and what do portfolio managers do when AI models signal contradicting information to their assessments.

REFERENCES

- Al Mahruqi, A. (2025). Artificial intelligence adoption in Gulf cybersecurity and financial institutions: Governance and capability implications. Journal of Digital Transformation Studies, 4(2), 55-72.
- Arrieta, A. B., Diaz-Rodriguez, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., Garcia, S., Gil-Lopez, S., Molina, D., Benjamins, R., Chatila, R., & Herrera, F. (2020). Explainable artificial intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. Information Fusion, 58, 82-115.
- Basel Committee on Banking Supervision. (2024). Digitalisation of finance. Bank for International Settlements.
- Bussmann, N., Giudici, P., Marinelli, D., & Papenbrock, J. (2021). Explainable AI in fintech risk management. Frontiers in Artificial Intelligence, 3, 26.
- Chen, N., Ribeiro, B., & Chen, A. (2020). Financial credit risk assessment: A recent review. Artificial Intelligence Review, 54, 1-23.
- European Banking Authority. (2020). Report on big data and advanced analytics. EBA.
- European Banking Authority. (2021). Discussion paper on machine learning for IRB models. EBA.
- Financial Stability Board. (2024). The financial stability implications of artificial intelligence. FSB.
- FinTech Saudi. (2024). Annual report: The fintech ecosystem in Saudi Arabia. FinTech Saudi.
- Goodell, J. W., Kumar, S., Lim, W. M., & Pattnaik, D. (2021). Artificial intelligence and machine learning in finance: Identifying foundations, themes, and research clusters. International Review of Financial Analysis, 73, 101681.
- International Organization for Standardization. (2023). ISO/IEC 23894: Information technology - Artificial intelligence - Guidance on risk management. ISO.
- Khandani, A. E., Kim, A. J., & Lo, A. W. (2020). Consumer credit-risk models via machine-learning algorithms. Journal of Banking and Finance, 34, 2767-2787.
- Kou, G., Chao, X., Peng, Y., Alsaadi, F. E., & Herrera-Viedma, E. (2021). Machine learning methods for systemic risk analysis in financial sectors. Technological and Economic Development of Economy, 27(5), 1139-1168.
- Kumar, S., Sharma, D., Rao, S., Lim, W. M., & Mangla, S. K. (2023). Past, present, and future of sustainable finance: Insights from big data analytics through machine learning of scholarly research. Annals of Operations Research, 1-44.
- Li, X., Yang, X., Zhang, H., & Liu, C. (2022). Credit risk prediction using machine learning and explainable artificial intelligence: A comparative study. Expert Systems with Applications, 198, 116831.
- Mashrur, A., Luo, W., Zaidi, N. A., & Robles-Kelly, A. (2020). Machine learning for financial risk management: A survey. IEEE Access, 8, 203203-203223.
- Ministry of Finance. (2023). Financial Sector Development Program: Overview and strategic objectives. Government of Saudi Arabia.
- Mittelstadt, B. (2021). Principles alone cannot guarantee ethical AI. Nature Machine Intelligence, 3, 10-17.
- National Institute of Standards and Technology. (2023). Artificial Intelligence Risk Management Framework (AI RMF 1.0). U.S. Department of Commerce.
- OECD. (2024). Regulatory approaches to artificial intelligence in finance. OECD Publishing.
- Personal Data Protection Law. (2021). Royal Decree No. M/19 and subsequent implementing regulations. Kingdom of Saudi Arabia.
- Rudin, C., Chen, C., Chen, Z., Huang, H., Semenova, L., & Zhong, C. (2022). Interpretable machine learning: Fundamental principles and 10 grand challenges. Statistics Surveys, 16, 1-85.
- SAMA. (2022). Open Banking Framework. Saudi Central Bank.

- SAMA. (2023). Rules for practicing finance activities and digital finance governance updates. Saudi Central Bank.
- Saudi Data and AI Authority. (2023). AI Ethics Principles. SDAIA.
- Siddiqui, A., & Rivera, C. A. (2024). Explainability, fairness and accountability in AI-based credit scoring: A review of governance controls. Journal of Risk and Financial Management, 17(4), 158.
- Truby, J., Brown, R., Dahdal, A., & Ibrahim, I. (2022). Banking on AI: Mandating a proactive approach to AI regulation in the financial sector. Law and Financial Markets Review, 16(1), 45-62.
- Vision 2030. (2024). Vision 2030 annual report and financial sector transformation progress. Government of Saudi Arabia.
- World Bank. (2022). Financial inclusion, digital finance and consumer protection: Policy considerations for emerging markets. World Bank.
- Zetzsche, D. A., Arner, D. W., Buckley, R. P., & Tang, B. (2020). Artificial intelligence in finance: Putting the human in the loop. University of Hong Kong Faculty of Law Research Paper, 2020/006.