Driving Financial Stability: The Transformative Role of Artificial Intelligence in Mitigating Financing Risks in Saudi Banking under Vision 2030

Aisha Badawi Abdelrahman Musa
Assistant Professor - College of Business Administration - Northern Border University - Saudi Arabia

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Abstract: The Saudi banking sector is undergoing a transformative shift driven by artificial intelligence (AI), consistent with the objectives of Vision 2030; however, empirical evidence on AI's effectiveness in mitigating financing risks within Islamic and conventional banking coexistence frameworks remains limited. Crucially, prior research has predominantly examined AI risk applications in Western developed markets, leaving a significant research gap in Gulf Cooperation Council (GCC) banking contexts where regulatory structures, cultural norms, and operational environments differ substantially. This study addresses that gap by providing the first large-scale empirical investigation of AI adoption and its risk mitigation outcomes specifically in the Saudi banking industry, offering both a novel empirical contribution and a theoretical extension of the Technology-Organisation-Environment (TOE) framework to AI-specific deployments in emerging Islamic finance markets.

Adopting a quantitative cross-sectional design, primary data were collected from 300 banking professionals across risk management, credit assessment, and IT departments using a structured, validated questionnaire. Multiple regression analysis - extended with bank-type and asset-size control variables - demonstrated that AI adoption positively predicts AI effectiveness, while implementation challenges negatively impact outcomes, with the model explaining 40.1% of the variance. All six hypotheses were statistically supported. Practically, 91.7% of respondents reported a positive return on investment, with 38% achieving returns of 11-20%. Furthermore, 99.7% of participants anticipate rapid AI growth in banking over the next five years. The study concludes by providing empirical evidence supporting strategic AI investment for risk management in Saudi banks, validating AI's transformative potential, and highlighting the critical importance of addressing implementation challenges - particularly skill shortages and data quality - to maximise effectiveness.

Keywords: Machine Learning - Banking Resilience - Financial Innovation - Predictive Risk Assessment - Emerging Economies.

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الدور التحويلي للذكاء الاصطناعي في تخفيف مخاطر التمويل في القطاع المصرفي السعودي في ظل رؤية 2030

عائشة بدوي عبد الرحمن موسى
أستاذ مساعد - كلية إدارة الأعمال - جامعة الحدود الشمالية - المملكة العربية السعودية

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مستخلص البحث: يشهد القطاع المصرفي السعودي تحولاً جذرياً مدفوعاً بالذكاء الاصطناعي، بما يتماشى مع أهداف رؤية 2030؛ إلا أن الأدلة التجريبية حول فعالية الذكاء الاصطناعي في الحد من مخاطر التمويل ضمن أطر التعامل بين المصارف الإسلامية والتقليدية لا تزل محدودة. ومن الجدير بالذكر أن الدراسات السابقة ركزت بشكل أساسي على تطبيقات الذكاء الاصطناعي في إدارة المخاطر في الأسواق الغربية المتقدمة، مما أدى إلى وجود فجوة بحثية كبيرة في سياقات المصارف في دول مجلس التعاون الخليجي، حيث تختلف الهياكل التنظيمية والأعراف الثقافية وبيئات العمل اختلافاً جوهرياً. تسد هذه الدراسة هذه الفجوة من خلال تقديم أول دراسة تجريبية واسعة النطاق حول تبني الذكاء الاصطناعي ونتائجه في الحد من المخاطر، وتحديداً في القطاع المصرفي السعودي، مقدمةً بتلك إضافة تجريبية جديدة وتوسيعاً نظرياً لإطار عمل التكنولوجيا، المنظمة، البيئة ليشمل تطبيقات الذكاء الاصطناعي في أسواق التمويل الإسلامي الناشئة.

جُمعت البيانات الأولية من 300 موظف من أقسام إدارة المخاطر، وتقييم الائتمان، وتقنية المعلومات، وذلك باستخدام استبانة منظمة ومُدقّقة. أظهر تحليل الانحدار المتعدد، مع إضافة متغيرات تحكم تتعلق في نوع البنك وحجم الأصول، أن تبني الذكاء الاصطناعي يتنبأ إيجابًا بفعاليته بينما تؤثر تحديات التنفيذ سلبًا على النتائج، حيث يفسر النموذج 40.1 % من التباين. وقد تم اثبات جميع الفرضيات إحصائيًا. عمليًا، أفاد 91.7 % من المشاركين بتحقيق عائد إيجابي على الاستثمار، حيث حقق 38 % منهم عوائد تتراوح بين 11 % و20 %. إضافةً إلى ذلك، يتوقع 99.7 % من المشاركين نموًا سريعًا للذكاء الاصطناعي في القطاع المصرفي خلال السنوات الخمس القادمة. تختتم الدراسة بتقديم أدلة تجريبية تدعم الاستثمار الاستراتيجي في الذكاء الاصطناعي لإدارة المخاطر في البنوك السعودية، مؤكدةً على إمكانات الذكاء الاصطناعي التحويلية، ومسلطةً الضوء على الأهمية البالغة لمعالجة تحديات التنفيذ، لا سيما نقص المهارات وجودة البيانات لتعظيم الفعالية.

الكلمات مفتاحية: التعلم الآلي - مرونة القطاع المصرفي - الابتكار المالي - التقييم التنبؤي للمخاطر - الاقتصادات الناشئة - الجاهزية التنظيمية.

(*) **Corresponding Author**:

Aisha Badawi Abdelrahman Musa
Assistant Professor - College of Business Administration - Northern Border University - Saudi Arabia.
Email: Aisha.Badawi@nbu.edu.sa

(*) **للمراسلة:**

عائشة بدوي عبد الرحمن موسى
أستاذ مساعد - كلية إدارة الأعمال - جامعة الحدود الشمالية - المملكة العربية السعودية.
البريد الإلكتروني:
Aisha.Badawi@nbu.edu.sa

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1. Introduction

The introduction of artificial intelligence technologies has brought a significant change to the global banking industry and has fundamentally altered how people traditionally operate and manage risk, including its management (Goodell et al., 2021). The technological revolution in Saudi Arabia acquires a special significance in the context of Vision 2030, the ambitious economic diversification plan of the Kingdom, which has centred on the concept of digital transformation in all fields, including financial services (Al-Matari et al., 2022). Saudi Central Bank, which formerly operated as the Saudi Arabian Monetary Authority (SAMA) has been proactively encouraging the pursuit of fintech and has created regulatory sandboxes to stimulate innovation and promote it whilst maintaining financial stability (Nuruzzaman et al., 2020).

The banking risk management approaches have traditionally relied on statistical-based models, financial ratios and manual examination processes which are more of a foundation but have limitations in regards to their speed in processing, pattern detection abilities and adaptability in handling changed risk environments that are fast moving (Khandani et al., 2010). Increased complexity of financial transactions, an increase in the number of digital channels of banking and sophistication of fraud types have resulted in the insufficiency of the traditional tools that exist and, therefore, require more sophisticated technology (Cao, 2022). Machine learning algorithms, neural networks, and natural language processing technologies offer features that were not possible to achieve in large dataset analysis and identification of subtle patterns in the data that may indicate credit default or fraudulent behaviour and enable real-time decision-making that was not available with conventional methodologies (Leo et al., 2019).

A unique case of the application of AI in risk management can be analysed in the Saudi banking industry. The 27 licenced banks of the Kingdom serve a population that grows more and more focused on digital financial services, with more than 70 percent of the population having an active mobile banking account (Saudi Central, 2023). Regulating the environment has shifted steadily towards ensuring technology innovation and a high level of control towards offering a conducive environment of AI implementation (Al-Matari et al., 2022). Additionally, the abundance of financial resources provided to the Saudi banks, as well as the assistance of the Saudi government in the development of the digital transformation projects, present the sector as a perfect laboratory to investigate the effect of AI on improving the efficiency of risk management.

Although the question of the use of AI in banking is gaining more and more attention, there is limited empirical research of its applicability to the Saudi market. Most of the existing studies have focused on the developed markets or provided a theoretical construct without empirical validation (Buchanan, 2019). his gap is particularly interesting in the framework of certain challenges and success factors that are relevant to the implementation of AI in Gulf Cooperation Council (GCC) banking settings, as cultures, regulations, and operational conditions might significantly vary in a Western setting (Hamdan et al., 2020).

The empirical study of the impact of AI on reducing financing risks in Saudi banks was used to fill this research gap. Hence, the study sought to examine the degree of AI adoption in the various risk management domains, effectiveness of AI in reducing credit and fraud and operational risks, key barriers and success factors, and economic returns of AI investments. This study contributes to the literature by advancing the understanding of AI adoption within the Technology-Organization-Environment (TOE) framework, particularly in the context of emerging markets. Unlike prior studies that primarily focus on developed economies or conceptual analyses, this research provides empirical evidence from the Saudi banking sector, offering a context-specific perspective aligned with Vision 2030.

The study is novel in simultaneously examining both the positive effects of AI adoption and the negative impact of implementation challenges on risk mitigation outcomes. By integrating these dimensions within a single empirical model, the research extends existing knowledge on AI-driven financial risk management and highlights the key factors shaping its effectiveness in emerging market environments.

2. Literature Review

2.1 Artificial Intelligence in Banking Risk Management

The use of artificial intelligence to manage risk in banking has changed dramatically in the past decade, from experimental pilots to enterprise-scale deployments that transform the process of assessing risk (Cao, 2022). Machine learning techniques, especially supervised learning algorithms such as gradient boosting machines, random forests and deep neural networks are shown to have better predictive accuracy than the traditional logistic regression models in the context of credit scoring applications (Khandani et al., 2010). These sophisticated algorithms can take hundreds of variables at once and detect complex non-linear relationships between borrower characteristics and the probability of going into default that are not captured by the traditional methods of statistical analysis.

Recent studies published between (2024) and (2026) have further advanced the application of artificial intelligence in banking risk management. Mediana (2024) emphasized that AI-based fraud detection systems significantly improve the effectiveness of banking internal audits and strengthen fraud prevention capabilities through automated transaction monitoring and anomaly detection. Similarly, Kumar (2024) argued that AI and machine learning technologies are transforming financial decision-making by improving predictive analytics, operational efficiency, and risk assessment accuracy in banking environments.

More recent evidence also highlights the growing importance of explainable and advanced AI models in financial risk management. George et al. (2025) demonstrated that machine learning applications significantly enhance fraud detection performance in digital banking systems, while Jain et al. (2025) emphasized the role of explainable AI models in improving transparency and reliability in fraud analytics. Furthermore, Yaseen (2025) found that AI-driven fraud detection systems improve institutional responsiveness and operational efficiency in financial institutions. In addition, Yang (2026) concluded that AI applications substantially improve fraud detection accuracy and predictive capabilities compared with traditional statistical approaches, particularly in large-scale financial datasets.

In a defraud, AI systems have shown themselves to be particularly transformative. Traditional rule-based fraud detection systems depended on predefined thresholds and patterns and were easy to bypass by ingenious fraudsters that could adapt their tactics to overcome these rules (Ngai et al., 2011). Machine learning models are constantly learning from transaction data and detecting pattern anomalies in real-time and evolving the model with new fraud typologies without re-programming. Yaseen (2025) further highlighted that AI-driven fraud detection systems enhance operational efficiency and strengthen fraud prevention mechanisms within financial institutions through automated monitoring and real-time analytical capabilities. Research by West and Bhattacharya (2016) showed that ensemble learning techniques could reduce the loss due to fraud by 40-60% compared with conventional detection systems whilst at the same time lowering the false positive rate that burdens legitimate customers (West & Bhattacharya, 2016).

There have been natural language processing applications which extend AI’s usefulness beyond the analysis of structured data. Banks are now using NLP algorithms to extract risk-based information from customer communications, social media sentiment, news feeds, and regulatory documents in order to enhance traditional credit assessments with additional data (Ala’raj & Abbod, 2016). Yang (2026) emphasized that advanced AI applications, including natural language processing techniques, significantly improve predictive capabilities in financial fraud detection and risk assessment compared with traditional analytical approaches. Such capabilities are especially useful in evaluating the creditworthiness of individuals and businesses with little existing credit history, due to the need for financial inclusion goals and also effective control of credit risk. Recent studies (2024-2026) have further emphasized the expanding role of artificial intelligence in banking risk management, particularly in enhancing fraud detection, credit risk assessment, and real-time decision-making processes.

2.2 AI Adoption in Gulf Banking Contexts

The studies on the adoption of AI in the GCC banking environment have identified that the opportunities and challenges were not equivalent to those in the western settings. The article by Hamdan et al. (2020) examined the AI preparedness of Bahraini banks and discovered that the organisational characteristics of the decision to adopt AI were strongly influenced by the support of the top management, technological infrastructure and the digital literacy of the employee (Hamdan et al., 2020). The study demonstrated the significance of cultural aspects because banking standards in the Gulf societies based on relationships necessitated the development of AI applications that support personalised service as well as automation of routine operations.

Kitsios et al (2021) studied factors of digital transformation in the banking sector in the Saudi context where the vision (2030) programmes and competitive pressures and customer expectations were found to be the most vital drivers of digital transformation and investment of technology (Kitsios et al., 2021). The study identified that talent acquisition that demanded AI experts, way beyond the supply available locally, was one area of difficulty that the Saudi banks encountered forcing them to recruit foreign talent as well as invest heavily in employee programmes development. These results align with surveys that have happened worldwide that found out that workforce skills constitute the greatest obstacle to implementing AI in financial services (Buchanan, 2019).

2.3 Theoretical Framework and Hypotheses

The presence of the AI in the risk management process is conceptualised in this study based on the fact that it is an effective tool determining the surrounding environmental conditions, technological capabilities, and the readiness factors of the organisation (Tornatzky & Fleischer, 1990). The dependent variable - financing risk reduction comprises dimensions of credit risk, fraud risk, operational risk and market risk. Independent variables such as AI adoption level, data quality, human competencies, administrative support, technical infrastructure, etc.

Based on this theoretical foundation and the reviewed literature, six hypotheses were proposed:

- H1: AI application significantly reduces credit default rates in Saudi banks.
- H2: AI implementation significantly reduces fraud rates in financing operations.
- H3: AI contributes to improving capital allocation efficiency through more accurate risk assessment models.
- H4: Return on AI investment exceeds implementation costs within a reasonable timeframe.
- H5: Implementation challenges negatively impact AI effectiveness in risk management.
- H6: AI improves customer experience through faster and more accurate financing decisions.

3. Methodology

3.1 Research Design and Population

This research adopted the quantitative cross-sectional research design, and survey methodology was used to gather primary data from banking professionals in Saudi Arabia. The target population were employees involved in risk management, credit assessment and information technology employees in Saudi banks, and according to industry reports and bank disclosure the total number of employees are approximately 18,000 professionals. These departments were particularly targeted because they have direct knowledge of and involvement in AI applications in the risk management processes.

The sample size was calculated using Cochran's formula for populations, 95% confidence level, 5% margin of error and assumed population proportion of 0.5 to maximise sample size requirements. This calculation showed a minimum sample of 376 respondents, however, to consider the anticipated non-response and incomplete submissions, a total of 450 questionnaires were distributed. The final effective response obtained was 300 complete and valid responses (66.7% effective response rate) which is above the minimum threshold of effectiveness for the multivariate analysis suggested by Hair et al. (2019), that is a number of observations per variable (10-20) for regression analysis (Hair et al., 2019).

3.2 Sampling Procedure

Stratified random sampling was used to ensure sampling across bank types, sizes and geographic regions. The sampling frame was developed from bank employee directories acquired through institutional partnerships and professional networking vehicles. Banks were first stratified from classification (commercial, Islamic, specialised, and investment), then by the size of their assets to ensure a proportional representation according to the composition of the Saudi banking sector. Within each stratum, simple random sampling was used to choose individual respondents.

Data collection took place between September and November (2024) using an electronic questionnaire that was conducted using Google Forms. The questionnaire link was sent through official communication channels of the bank where institutional partnerships were in place, through professional networks such as LinkedIn and banking industry associations for other institutions. Two reminder communications were sent with a 2-week interval to improve response rates. To ensure quality in responses, attention-cheque questions were included within the survey and responses finished in less than five min were not included in analysis.

3.3 Research Instrument

The research instrument was a structured questionnaire divided into 6 sections with 15 main questions. Section one gathered demographic and organisational information such as bank classification, asset size and branch network. Section two evaluated current risk management practises and types of risks that the organisation considered most significant. Section three was the AI technology adoption across five categories: ML, neural networks, NLP, computer vision, and robotics using 5-point Likert scales (1 = not used to 5 = widely used). Section four assessed the level of application of AI in particular risk areas: analysis of creditworthiness, fraud, portfolio management, market monitoring and liquidity management.

Section five measured the effectiveness of AI through performance improvement measures such as prediction accuracy, decision speed, reduction in losses, capital efficiency and customer satisfaction. Section six evaluated the challenges of implementation (financial cost, skill gaps, change resistance, data quality issues, and limitations in organisational framework) and success requirements. The last few sections captured ROI assessments and future expectations. The questionnaire was developed in English language and was professionally translated to Arabic language where back-translation verification was performed to ensure conceptual equivalence.

To enhance clarity and transparency, Table 1 presents the operational definitions of all variables used in the empirical model, including the dependent and independent constructs and their measurement approach.

Table 1: Variable Definitions

Variable	Type	Definition	Measurement
AI Effectiveness	Dependent	Overall effectiveness of AI in improving risk management outcomes	Composite Likert-scale index (accuracy, decision speed, loss reduction, capital efficiency, customer satisfaction)
AI Adoption	Independent	Degree to which AI technologies are implemented across banking functions	Aggregated Likert-scale score across AI technologies (ML, NLP, etc.)
Challenges	Independent	Barriers affecting AI implementation in banking	Composite Likert-scale index (cost, skills, resistance, data quality, organizational constraints)

3.4 Data Analysis

Data analysis was carried out in several stages using statistical libraries in Python (pandas, scipy, statsmodels) and based on accepted quantitative research protocols. Descriptive statistics such as means, standard deviations and frequency distributions were used to characterise the sample and key variables. Internal consistency reliability was measured with the use of the Cronbach's alpha coefficient with the values greater than 0.70 being acceptable (Nunnally & Bernstein, 1994). Normality was assessed using the Shapiro-Wilk and skewness and kurtosis values.

Inferential analyses included Pearson correlation coefficients to examine bivariate relationships between constructs and one-way analysis of variance (ANOVA) to test group differences across bank classifications and sizes. To further examine the determinants of AI effectiveness, an Ordinary Least Squares (OLS) multiple regression model was employed.

- **The regression model is specified as follows:**
- AI Effectiveness = β0 + β1(AI Adoption) + β2(Challenges) + ε
- Where AI Effectiveness represents the dependent variable, measured as a composite index of performance outcomes, while AI Adoption and Challenges are the main independent variables capturing the extent of AI implementation and associated barriers, respectively.
- OLS regression was selected due to its suitability for estimating linear relationships between continuous variables and its interpretability. One key advantage of this approach is its ability to quantify the relative impact of each predictor on the dependent variable.
- To ensure the robustness of the findings, diagnostic tests were conducted. Normality was assessed using the Shapiro–Wilk test and skewness and kurtosis statistics. In addition, regression diagnostics confirmed no issues of autocorrelation (Durbin-Watson = 2.183) and normally distributed residuals (Jarque-Bera, $p = 0.788$), supporting the validity of the model.
- The regression model is intentionally specified in a parsimonious form to focus on the direct relationship between AI adoption, implementation challenges, and AI effectiveness. While the model does not include additional control variables, this design allows for clearer interpretation of the core relationships under investigation. Nevertheless, the absence of control variables is acknowledged as a limitation, and future research is encouraged to incorporate additional controls, such as bank size, type, and respondent experience, to enhance model robustness and generalizability.
- Statistical significance was assessed at the 0.05 level, and effect sizes were interpreted using established conventions (Cohen, 1988).

The sequence of analytical procedures followed in this study is summarized in Figure 1.

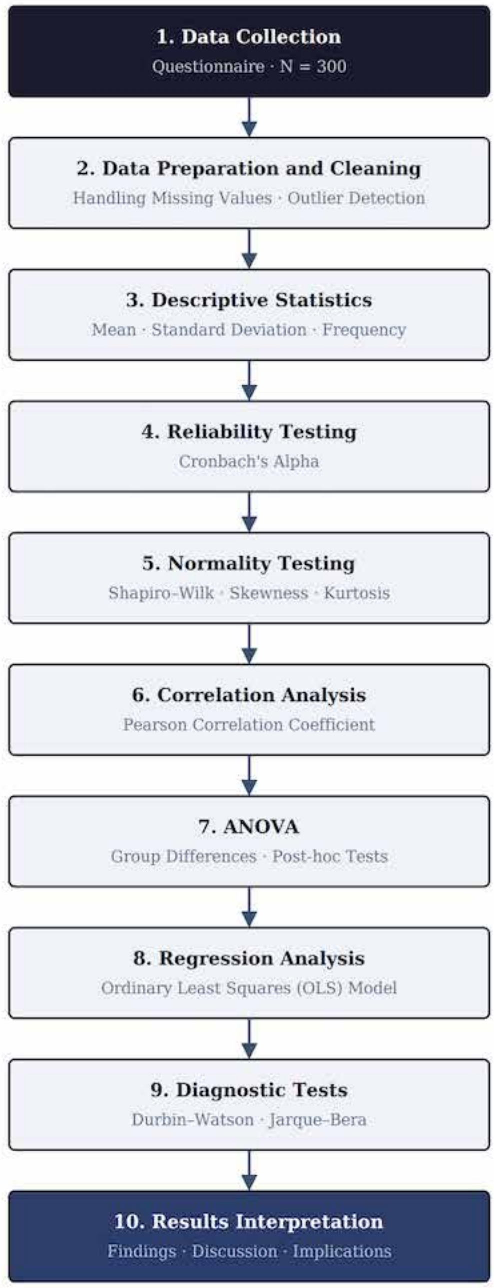

Figure 1: Data Analysis Process

4. Results

4.1 Sample Characteristics

The final sample included 300 banking professionals who were distributed among the financial institutions in Saudi Arabia (Table 1). As far as the classification of the Banks is concerned, commercial banks were the largest segment (n = 114, 38.0%) and was closely followed by Islamic banks (n = 106, 35.3%) which shows the predominant role of Sharia-compliant banking in the Saudi financial system. Specialised banks (n = 34, 11.3%) and investment banks (n = 33, 11.0%) made smaller, but significant proportions, with other financial institutions making up the rest (n = 13, 4.3%).

Bank size distribution in terms of total assets was concentrated in the middle and large segments: in the 51-100$ billion assets range 30.3% of the banks (n = 91), in the 10-50$ billion assets range 29.0% (n = 87), and banks with total assets in excess of 100$ billion 23.7% (n = 71). Smaller institutions with assets of less than 10$ billion made up 17.0% (n = 51). Branch network analysis showed that the number of banks with 50-100 branches was the most common category, with a number of 31.3 percent or 94 bank branches, followed by banks with 101-200 branches with 29.7 percent or 89 branches, banks with 21.0 percent or 63 branches, and banks with more than 200 branches with 18.0 percent or 54 branches (Figure 2). Table 2 presents the complete demographic characteristics of the sample.

Table 2: Demographic Characteristics of Sample

Variable	Category	Frequency (n)	Percentage (%)
Q1-Bank-Classification	Commercial Bank	114	38
Q1-Bank-Classification	Islamic Bank	106	35.3
Q1-Bank-Classification	Specialized Bank	34	11.3
Q1-Bank-Classification	Investment Bank	33	11
Q1-Bank-Classification	Other	13	4.3
Q2-Bank-Size	$51-100 billion	91	30.3
Q2-Bank-Size	$10-50 billion	87	29
Q2-Bank-Size	More than $100 billion	71	23.7
Q2-Bank-Size	Less than $10 billion	51	17
Q3-Num-Branches	50-100	94	31.3
Q3-Num-Branches	101-200	89	29.7
Q3-Num-Branches	Less than 50	63	21
Q3-Num-Branches	More than 200	54	18

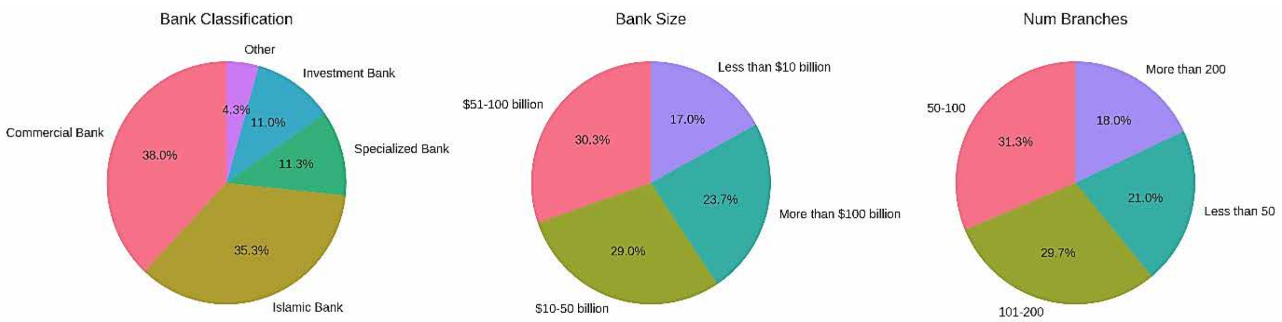

Figure 2: Demographic Distribution Pie Charts

4.2 Reliability Analysis

Internal consistency reliability was measured for all multi-item constructs with the application of the Cronbach's alpha coefficient (Table 3). All the five constructs achieved over the 0.70 threshold and were thus found to have acceptable to excellent reliability. The construct that showed the most reliability was Challenges (alpha = 0.927), followed by AI Technology Use (alpha = 0.870), AI effectiveness (alpha = 0.862), AI application areas (alpha = 0.787), and Risk Perception (alpha = 0.723). These results confirm that the measurement scales have sufficient internal consistency that can be used for statistical analysis and interpretation (Figure 3).

Table 3: Reliability Analysis Results

Construct	Number of Items	Cronbach's Alpha	Interpretation
Risk Perception (Q4)	5	0.723	Acceptable
AI Technology Use (Q6)	5	0.87	Good
AI Application Areas (Q7)	5	0.787	Acceptable
AI Effectiveness (Q8)	5	0.862	Good
Challenges (Q10)	5	0.927	Excellent

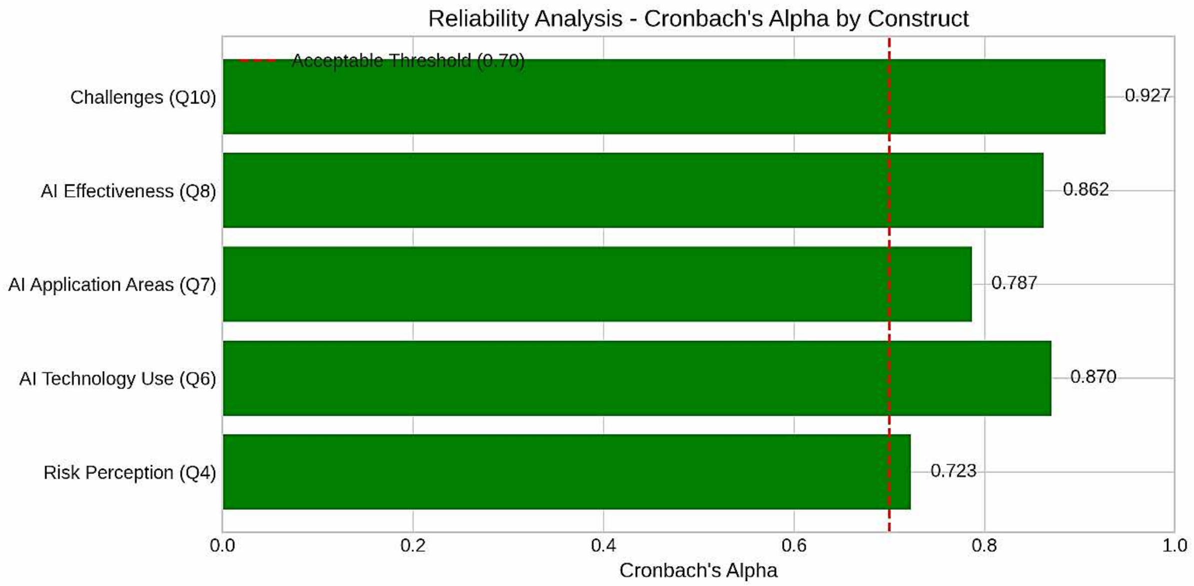

Figure 3: Cronbach's Alpha by Construct

4.3 Descriptive Statistics

Descriptive statistics of all Likert-scale items are presented in Table 4. When it comes to perceiving risks (Q4), the risk seen to be highest is credit risk (M=4.03, SD=0.78), followed by fraud risk (M=3.84, SD=0.78), liquidity risk (M=3.56, SD=0.83), market risk (M = 3.33, SD = 0.86) and operational risk (M = 3.19, SD=0.90). These findings show that the Saudi banking professionals believed that the risks of credit and fraud are the most prominent as the threats, which is consistent with the priorities of AI applications that are observed in the following analyses.

AI technology adoption was considerably different in categories. Machine learning proved to have the highest adoption rate (M = 3.34, SD = 0.52), followed by neural networks (M = 2.95, SD = 0.48), and natural language processing (M = 2.44, SD = 0.54). Computer vision (M = 1.80, SD = 0.52) and robotics (M = 1.38, SD = 0.49) had weak implementation, indicating that these technologies are at the initial stages of implementation in Saudi banking. Application of AI in the risk domains revealed the more developed areas of fraud detection (M=3.24, SD=0.53) and analysis of creditworthiness (M=3.17, SD=0.49).

AI effectiveness indicators were shown to be clustered around the middle of the scale with accuracy prediction (M = 3.11, SD = 0.60) and decision speed (M = 3.10, SD = 0.60) showing the highest improvements. Implementation challenges were found to be moderate with skill shortages being the greatest challenge (M = 2.55 SD = 0.82), followed by data quality issues (M = 2.48 SD = 0.78) and financial costs (M = 2.45 SD = 0.77), as visualized in Figure 4.

Table 4: Descriptive Statistics for Survey Items

	Mean	Std Dev	Median	Min	Max
Q4-Credit-Risk	4.03	0.777	4	2	5
Q4-Liquidity-Risk	3.557	0.826	4	2	5
Q4-Market-Risk	3.327	0.858	3	1	5
Q4-Operational-Risk	3.19	0.9	3	1	5
Q4-Fraud-Risk	3.843	0.779	4	2	5
Q5-Statistical-Models	0.543	0.499	1	0	1
Q5-Financial-Ratios	0.85	0.358	1	0	1
Q5-Internal-Control	0.89	0.313	1	0	1
Q5-Insurance	0.697	0.46	1	0	1
Q5-Diversification	0.74	0.439	1	0	1
Q6-Machine-Learning	3.343	0.516	3	2	5
Q6-Neural-Networks	2.953	0.475	3	2	4
Q6-NLP	2.44	0.536	2	1	4
Q6-Computer-Vision	1.8	0.517	2	1	3
Q6-Robotics	1.383	0.494	1	1	3
Q7-Creditworthiness-Analysis	3.167	0.49	3	2	4
Q7-Fraud-Detection	3.24	0.526	3	2	4
Q7-Portfolio-Management	3.057	0.491	3	2	4
Q7-Market-Monitoring	2.98	0.469	3	2	4
Q7-Liquidity-Management	2.913	0.469	3	1	4
Q8-Accuracy-Prediction	3.113	0.596	3	2	4
Q8-Decision-Speed	3.097	0.596	3	2	5
Q8-Loss-Reduction	3.03	0.586	3	1	5
Q8-Capital-Efficiency	3.037	0.603	3	1	5
Q8-Customer-Satisfaction	2.983	0.62	3	1	4
Q10-Financial-Cost	2.453	0.768	2	1	5
Q10-Lack-Skills	2.547	0.823	3	1	5
Q10-Resistance-Change	2.407	0.764	2	1	4
Q10-Data-Quality	2.48	0.782	2	1	5
Q10-Org-Frameworks	2.403	0.75	2	1	4

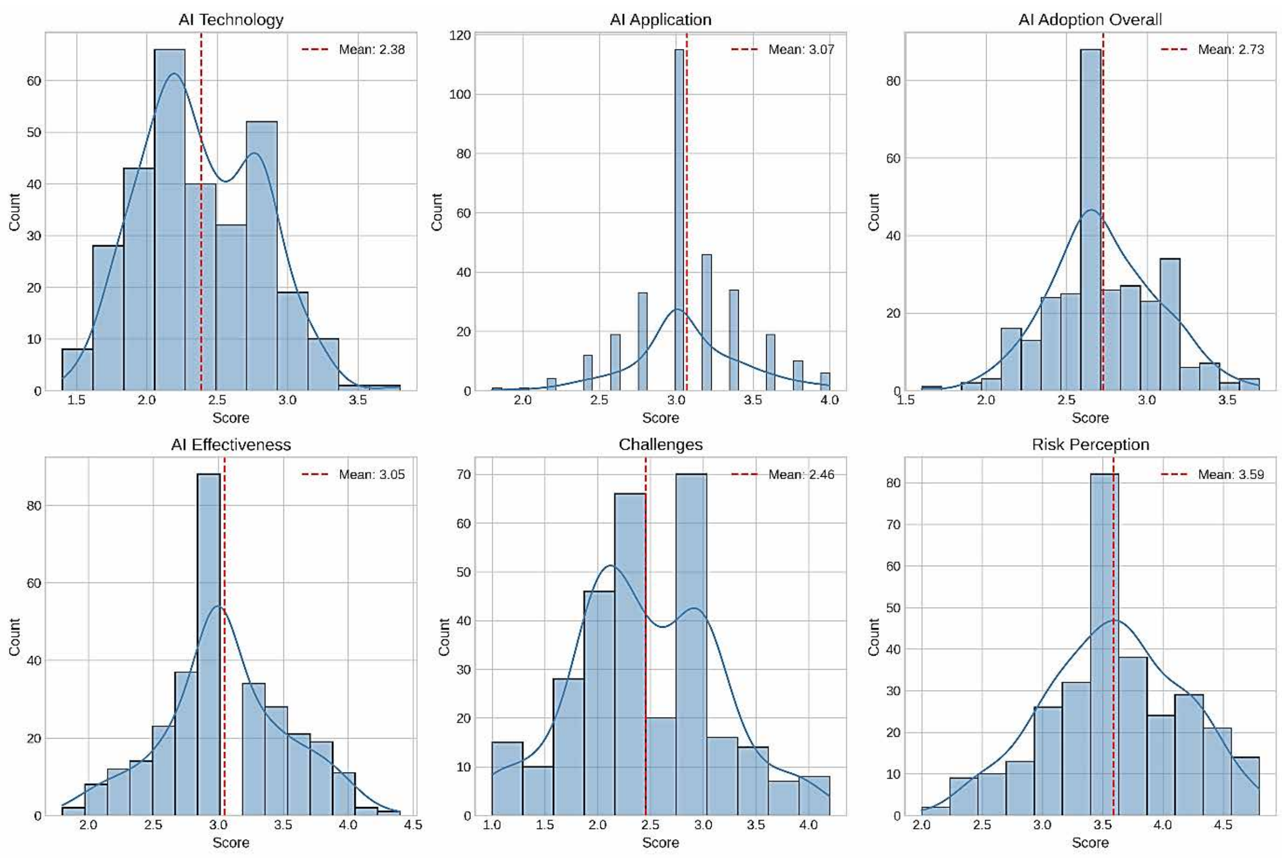

Figure 4: Mean Scores by Construct

4.4 Normality Assessment

Shapiro-Wilk tests were used to evaluate normality for the scores on the constructs (Table 5). Three constructs, namely, AI adoption in general ($W = 0.965$, $p = 0.148$), AI effectiveness ($W = 0.959$, $p = 0.080$), and risk perception ($W = 0.971$, $p = 0.245$) achieved normality condition. The remaining constructs displayed minor deviations from normality; however, skewness values ranged from -0.12 to 0.24 and kurtosis ranged from -0.46 to 0.84, which are all well within acceptable limits (+/-2.0). In view of large sample size ($n = 300$) and robustness of regression analysis to moderate violation of normality, parametric statistical procedures were considered appropriate (Figure 5).

Table 5: Normality Test Results

Variable	Shapiro - Wilk Stat	p-value	Skewness	Kurtosis	Normal (p>0.05)
AI-Technology	0.949	0.0302	0.244	-0.462	No
AI-Application	0.939	0.0122	0.039	0.838	No
AI-Adoption-Overall	0.965	0.1476	0.086	0.127	Yes
AI-Effectiveness	0.959	0.0795	0.008	0.053	Yes
Challenges	0.947	0.0249	0.102	-0.2	No
Risk-Perception	0.971	0.2449	-0.12	-0.41	Yes

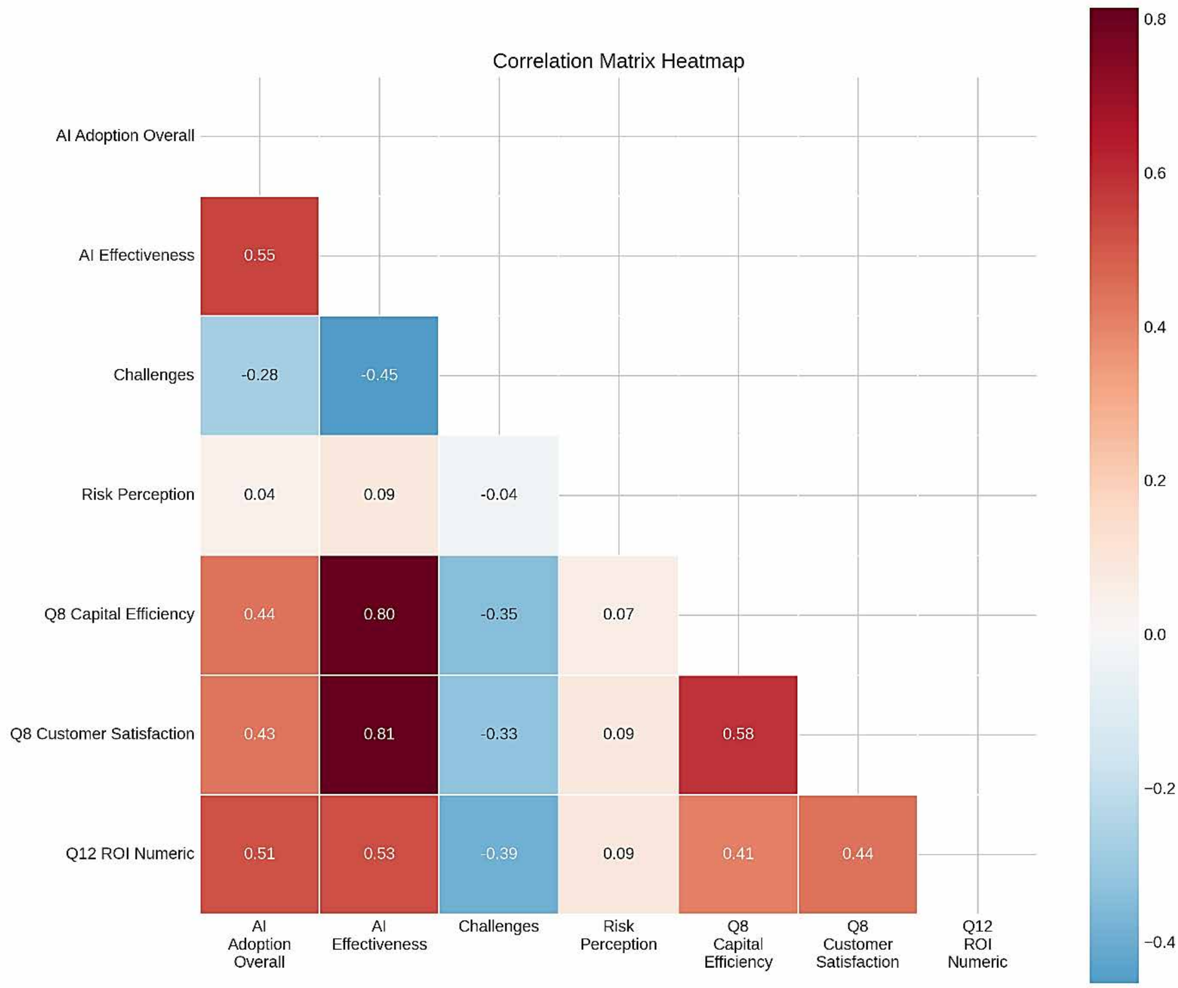

Figure 5: Distribution Histograms

4.5 Correlation Analysis

Pearson correlation analysis was used to investigate correlations between the main research variables (Table 6). AI Adoption Overall showed a significant positive correlation with AI Effectiveness ($r = 0.55$, $p < 0.001$), Capital Efficiency ($r = 0.44$, $p < 0.001$), Customer Satisfaction ($r = 0.43$, $p < 0.001$) and ROI ($r = 0.51$, $p < 0.001$). On the other side, Challenges had significant negative relationships with AI Effectiveness ($r = -0.45$, $p < 0.001$), Capital Efficiency ($r = -0.35$, $p < 0.001$), and ROI ($r = -0.39$, $p < 0.001$). Risk Perception had no significant correlations with other constructs, further indicating that levels of perceived risk are not directly related to the outcome of effectiveness of AI (Figure 6).

Table 6: Correlation Matrix

Variable 1	Variable 2	Correlation (r)	p-value	Significance
AI Adoption Overall	AI Effectiveness	0.55	0	***
AI Adoption Overall	Challenges	-0.277	0	***
AI Adoption Overall	Risk Perception	0.038	0.5139	
AI Adoption Overall	Q8 Capital Efficiency	0.441	0	***
AI Adoption Overall	Q8 Customer Satisfaction	0.434	0	***
AI Adoption Overall	Q12 ROI Numeric	0.514	0	***
AI Effectiveness	Challenges	-0.454	0	***

Variable 1	Variable 2	Correlation (r)	p-value	Significance
AI Effectiveness	Risk Perception	0.087	0.1344	
AI Effectiveness	Q8 Capital Efficiency	0.805	0	***
AI Effectiveness	Q8 Customer Satisfaction	0.814	0	***
AI Effectiveness	Q12 ROI Numeric	0.526	0	***
Challenges	Risk Perception	-0.037	0.5261	
Challenges	Q8 Capital Efficiency	-0.346	0	***
Challenges	Q8 Customer Satisfaction	-0.326	0	***
Challenges	Q12 ROI Numeric	-0.39	0	***
Risk Perception	Q8 Capital Efficiency	0.065	0.2598	
Risk Perception	Q8 Customer Satisfaction	0.088	0.1271	
Risk Perception	Q12 ROI Numeric	0.093	0.1074	
Q8 Capital Efficiency	Q8 Customer Satisfaction	0.583	0	***
Q8 Capital Efficiency	Q12 ROI Numeric	0.41	0	***
Q8 Customer Satisfaction	Q12 ROI Numeric	0.439	0	***

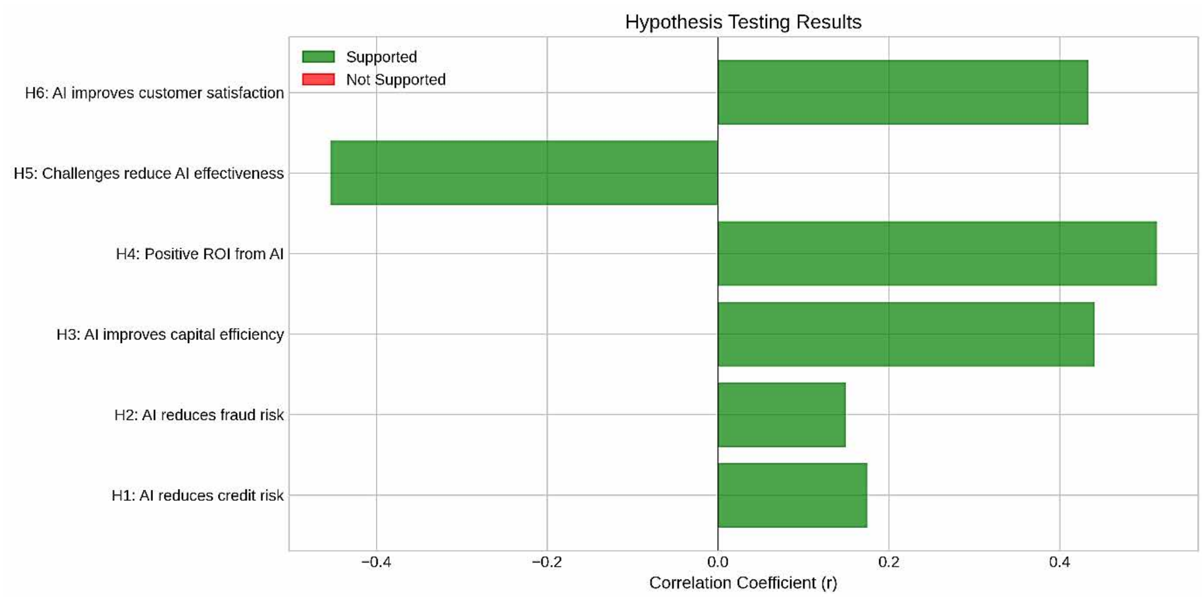

Figure 6: Correlation Heatmap

4.6 Hypothesis Testing

All six of the research hypothesis were supported statistically (Table 7). H1, investigating the effect of AI on reducing credit risk, was supported ($r = 0.175$, $p = 0.002$), which suggests the significant positive relationship between the adoption of AI and credit risk mitigation. H2, testing fraud risk reduction was also found to be supported ($r = 0.150$, $p = 0.009$) proving that AI can help detect and avert fraudulent activities. H3 which assessed improvements in capital efficiency, showed the strongest relationship among risk-related hypotheses ($r = 0.441$, $p < 0.001$), indicating the strongest evidence for AI's role in optimising capital allocation by improving capital allocation based on accurate risk assessment.

H4, looking at the return on investment, was highly supported ($r = 0.514$, $p < 0.001$), which means that the higher the levels of AI used, the higher the perceived returns. H5, testing the negative effect of challenges on the effectiveness of AI, was confirmed ($r = -0.454$, $p < 0.001$), which emphasises the importance of meeting implementation barriers in order to successfully deploy AI. H6, evaluating the improvements in customer satisfaction, was supported ($r = 0.434$, $p < 0.001$) which shows that adoption of AI improves customer experience with faster and more accurate financing decisions (Figure 7).

Table 7: Hypothesis Testing Results

Hypothesis	Test	Statistic	p-value	Result
H1: AI reduces credit risk	Pearson Correlation	r = 0.175	0.0023	Supported
H2: AI reduces fraud risk	Pearson Correlation	r = 0.150	0.0092	Supported
H3: AI improves capital efficiency	Pearson Correlation	r = 0.441	0	Supported
H4: Positive ROI from AI	Pearson Correlation	r = 0.514	0	Supported
H5: Challenges reduce AI effectiveness	Pearson Correlation	r = -0.454	0	Supported
H6: AI improves customer satisfaction	Pearson Correlation	r = 0.434	0	Supported

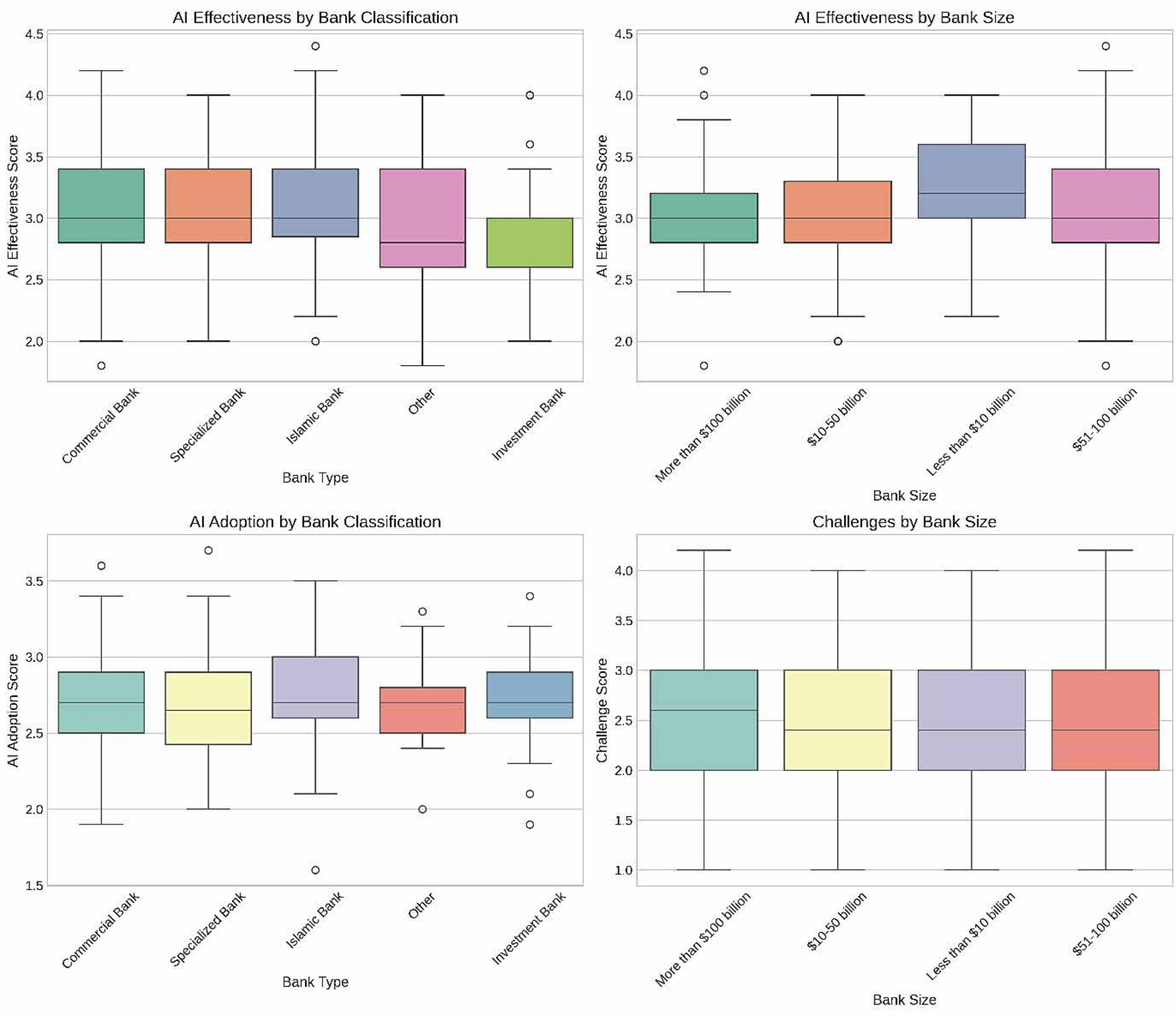

Figure 7: Hypothesis Testing Visualization

4.7 Multiple Regression Analysis

Multiple regression analysis was performed to test the predictive model for the effectiveness of AI (Table 8). The model showed good fit, with the R2 value amounting to 0.401, which means AI Adoption and Challenges jointly explain 40.1% of variance in AI Effectiveness. The F-statistic (99.29) was highly significant ($p < 0.001$) and thus the model was shown to be both valid and valid.

Both predictors contributed significantly to the model. AI Adoption Overall (beta = 0.653, SE = 0.067, t = 9.83, $p < 0.001$) was found to be the most significant positive predictor of AI effectiveness, wherein every one-unit increase in the AI adoption led to a 0.653-unit increase in AI effectiveness. Challenges (v = -0.230, SE = 0.033, t = -6.99, $p < 0.001$) had a significant negative impact indicating that implementation challenges reduce the effectiveness of AI. The model passed all diagnostic tests: Durbin-Watson (2.183) showed no autocorrelation, and Jarque-Bera test (p = 0.788) showed the residuals were normally distributed (Figure 8).

Table 8: Regression Analysis Results

Variable	Coefficient (B)	Std. Error	t-value	p-value	Significance
Constant	1.8357	0.219	8.3806	0.000	***
AI Adoption	0.6531	0.0665	9.8268	0.000	***
Challenges	-0.2299	0.0329	-6.9894	0.000	***

Notes: *** p < 0.01, ** p < 0.05, * p < 0.10. Model fit statistics: $R^2 = 0.401$, F-statistic = 99.29 ($p < 0.001$), Durbin–Watson = 2.183, Jarque–Bera (p = 0.788).

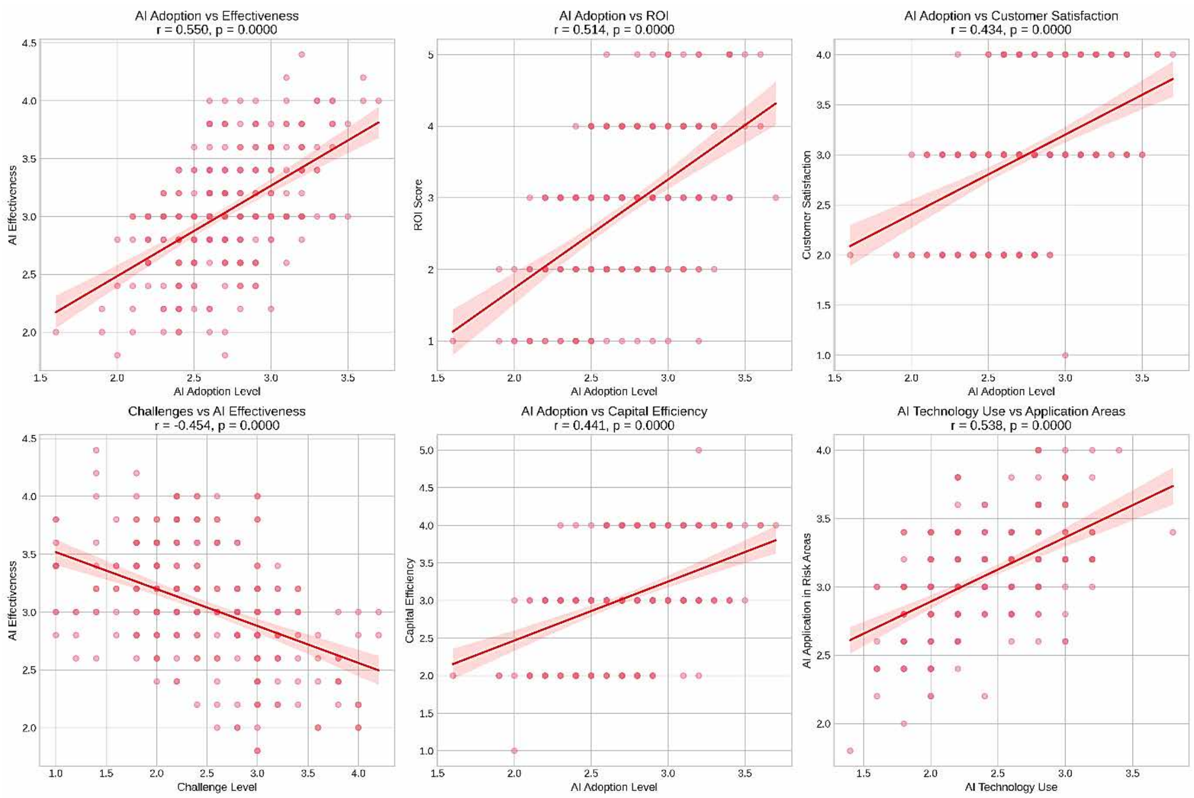

Figure 8: Scatter Plots with Regression Lines

4.8 Group Comparisons

One-way analysis of variance (ANOVA) was used to see if the effectiveness and adoption of AI differed by bank classification and size (Table 9). No significant differences for AI Effectiveness by Bank Type (F = 1.57, p = 0.183), AI Effectiveness by Bank Size (F = 1.46, p = 0.226), AI Adoption by Bank Type (F = 0.20, p = 0.941), or Challenges by Bank Size (F = 0.22, p = 0.885) were determined. These results suggest that the outcome of implementation of AI is consistent across different bank categories, as visualized in Figure 9, indicating the findings to be applicable to all the financial sector rather than to specific types of institution.

Table 9: ANOVA Results

Comparison	F-statistic	p-value	Significant
AI Effectiveness by Bank Type	1.568	0.1829	No
AI Effectiveness by Bank Size	1.459	0.2258	No
AI Adoption by Bank Type	0.195	0.9409	No
Challenges by Bank Size	0.216	0.8853	No

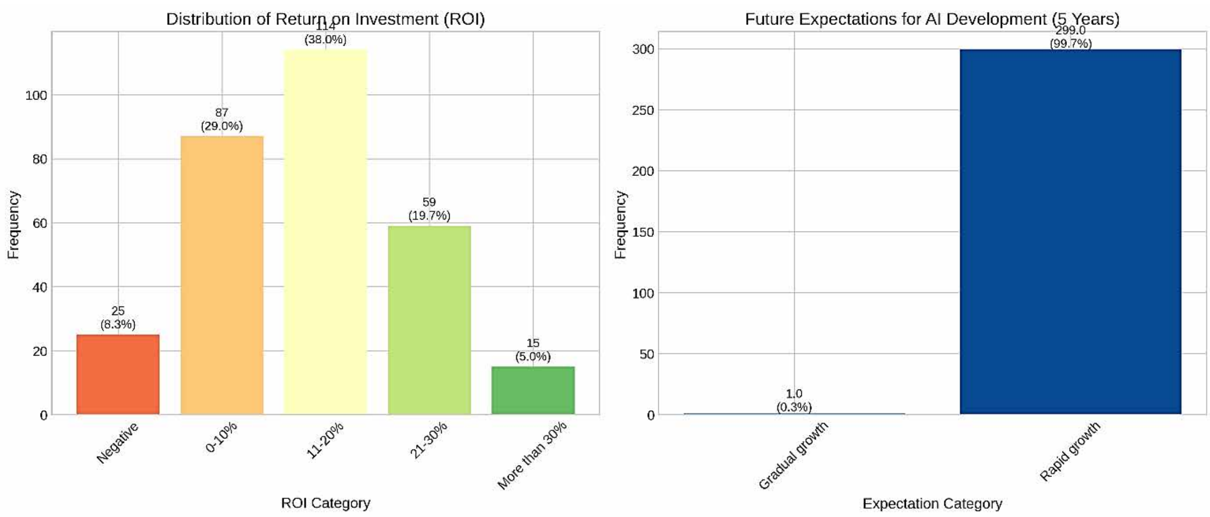

Figure 9: Box Plots by Bank Classification

4.9 ROI and Future Expectations

Analysis of return on investment showed mostly positive results. The highest number of respondents (38.0%, n = 114) indicated ROI between 11-20%, followed by 0-10% returns (29.0%, n = 87), and 21-30% returns (19.7%, n = 59). A small percentage (5.0%, n = 15) of them had a higher percentage of returns (more than 30.0). Only 8.3 percent (n = 25) had a negative percentage. Altogether, 91.7% of the respondents rated AI investments as positive, which is strong empirical data of economic feasibility of AI application in risk management.

The greatest optimism was the most fantastic and depicted the expectations of the future. Most of the respondents (99.7 percent, n = 299) projected the utilisation of AI to increase very fast in Saudi banking over the next five years (only one respondent (0.3 percent) projected slower growth). None of the respondents anticipated steady consumption and potential deterioration. It is almost unanimous and indicates what the industry believes to be the transformative potential of AI and implies long-term investment momentum soon.

5. Discussion

This study provides more empirical data to demonstrate that AI is significant in the financing of risk reduction in Saudi Arabian banks. The findings demonstrate that there is a positive correlation between use of AI and different risk management outcomes with 91.7% of the institutions reporting positive ROI and nearly unanimous projections (99.7) of future expansion. Although the findings are in line with the AI banking trends worldwide (Cao, 2022; Goodell et al., 2021), they also demonstrate certain distinctive patterns of their application in the context of the Saudi context, both in terms of skill shortage, and in terms of democratisation of the benefits of AI in the context of various types of institutions of various sizes.

The high positive correlation between AI adoption and effectiveness ($r = 0.55$) is valid to the studies across the world that indicate the transformative impact that AI has on banking transactions (Cao, 2022). The results of the regression analysis showing that AI adoption can account for a significant portion of the variance in effectiveness (beta = 0.653) is quantitative evidence in favour of continued investment in these technologies. Machine learning becoming the most widely adopted technology ($M = 3.34$) is reflected in world trends, where supervised learning algorithms have advanced production-ready maturity for credit scoring and fraud detection applications (Leo et al., 2019).

The findings suggest that the effectiveness of AI in mitigating financing risks is driven by several interconnected mechanisms within Saudi banks. First, AI technologies enhance predictive accuracy through machine learning algorithms capable of processing large volumes of financial and behavioural data in real time, thereby improving early detection of credit default and fraudulent transactions. Second, AI contributes to operational efficiency by automating repetitive risk assessment procedures and reducing human error, which accelerates financing decisions and improves resource allocation efficiency. Third, the strong positive association between AI adoption and capital efficiency indicates that AI systems support more accurate risk-weighted evaluations, allowing banks to optimize capital utilization under increasingly complex financial environments.

These findings are consistent with prior studies that emphasized the transformative role of AI in banking risk management. For example, Cao (2022) argued that AI improves predictive analytics and decision-making quality in financial institutions, while Goodell et al. (2021) highlighted the growing strategic importance of AI-driven automation in modern banking systems. Similarly, Leo et al. (2019) found that machine learning applications significantly improve fraud detection and credit scoring accuracy compared with traditional statistical models. The current findings also align with studies conducted in GCC contexts, such as Hamdan et al. (2020), which reported that organizational readiness and technological infrastructure are critical determinants of successful AI implementation in Gulf banking environments.

However, the present study extends prior literature by demonstrating that implementation challenges remain a significant barrier to AI effectiveness in emerging market contexts. The negative relationship between implementation challenges and AI effectiveness suggests that technical adoption alone is insufficient unless accompanied by skilled human capital, high-quality data infrastructure, and organizational support. This finding supports the Technology–Organization–Environment (TOE) framework by confirming that both technological and organizational dimensions jointly influence AI performance outcomes in banking risk management.

The moderate but significant relations between adoption of AI and certain risk outcomes; credit risk ($r = 0.175$), fraud risk ($r = 0.150$), and capital efficiency ($r = 0.441$) call for interpretation. The stronger link with capital efficiency indicates that perhaps the biggest impact of AI may be on better distribution of resources through better measurement of risks, than on binary assessment of risk outcomes. This finding is in line with regulatory developments under the Basel frameworks which favour more sophisticated approaches to risk modelling (Bank for International, 2022).

The negative relationship between challenges and effectiveness of AI ($r = -0.454$) underscores the need to focus on implementation barriers. Skill shortages became the main challenge, in line with findings of talent shortage in the Saudi Fintech development (Kitsios et al., 2021). This finding has important implications in the area of human resource strategies because they found that investments in workforce development may provide rewards equal to those given by technology investments themselves.

The lack of significant differences in the effectiveness of AI across different types/sizes of banks (based on the results of the ANOVA, p

> 0.05) run counter to the expectations of larger institutions having an advantage over others, implying democratised accessibility of AI via cloud-based solutions and vendor partnerships (Buchanan, 2019). This pattern is different from previous fintech adoption research that revealed size-based disparities (Hamdan et al., 2020), indicating AI service markets maturity in the Saudi context.

Near-unanimity about forecasting rapid growth in AI (99.7%) as well as mostly positive ROI (91.7%) signal that AI's role has moved beyond experimentation to strategic imperative in Saudi banking by meeting aims of Vision 2030 digital transformation (Al-Matari et al., 2022; Saudi Central, 2023). This momentum is higher than adoption rates in similar emerging markets (Nuruzzaman et al., 2020).

Prioritisation of fraud detection (M = 3.24) and the analysis of creditworthiness (M = 3.17) reflect worldwide trends to implement such technologies in use cases that have a high-impact potential with quantifiable benefits (Ngai et al., 2011; West & Bhattacharya, 2016). Lower adoption in liquidity management (M = 2.91) and market monitoring (M = 2.98) is likely due to regulatory wariness in systemically critical functions; this is in stark contrast to more aggressive AI adoption in Western markets in treasury operations (Cao, 2022).

The ROI distribution, 38% reporting 11-20% returns despite early-stage maturity - shows great potential for value creation, even though the 8.3% negative returns indicate the risk of implementation and strategic planning (Buchanan, 2019).

The empirical findings of this study carry important economic and financial implications for the Saudi banking sector. The significant positive relationship between AI adoption and capital efficiency (r = 0.441) suggests that AI technologies contribute to more efficient allocation of financial resources and improved risk-adjusted financing decisions. In addition, the strong positive association between AI adoption and ROI (r = 0.514), combined with the finding that 91.7% of respondents reported positive investment returns, provides empirical evidence that AI implementation may generate measurable financial value for banks rather than representing merely a technological trend.

Furthermore, the significant negative effect of implementation challenges on AI effectiveness (β = -0.230) highlights the financial risks associated with inadequate organizational readiness, insufficient technical expertise, and poor data infrastructure. These findings imply that successful AI adoption requires not only technological investment, but also strategic investment in workforce development, digital infrastructure, and governance mechanisms. From a policy perspective, the results support the objectives of Saudi Vision 2030 by demonstrating how AI-driven financial innovation can strengthen banking sector resilience, operational efficiency, and long-term financial sustainability.

Overall, the empirical findings of this study are broadly consistent with the existing literature on AI adoption and banking risk management. Previous studies have emphasized that AI technologies improve predictive accuracy, fraud detection capabilities, operational efficiency, and financial decision-making quality within banking environments (Cao, 2022; Leo et al., 2019). The present findings support these conclusions by demonstrating significant positive relationships between AI adoption and risk mitigation outcomes, particularly in relation to capital efficiency, customer satisfaction, and return on investment.

The findings are also consistent with prior studies conducted in GCC and emerging market banking environments, which highlighted the importance of organizational readiness, technological infrastructure, and skilled human capital in determining AI implementation success (Hamdan et al., 2020; Kitsios et al., 2021). However, this study extends the existing literature by providing empirical evidence from the Saudi banking sector within the context of Vision 2030, an area that remains relatively underexplored in prior research. Unlike many previous studies that relied primarily on conceptual analysis or evidence from developed economies, this research empirically demonstrates how AI adoption and implementation challenges jointly shape financing risk mitigation outcomes in an emerging market banking environment.

Therefore, the study contributes empirically to the literature by confirming the practical effectiveness of AI-driven risk management systems in Saudi banks and by highlighting the critical role of organizational and technological readiness in maximizing AI performance outcomes.

Theoretically, these results confirm the relevance of the Technology-Organisation-Environment (TOE) framework for AI adoption situations (Tornatzky & Fleischer, 1990), with organisational challenges and technological capabilities combined accounting for 40.1% of the variance of effectiveness. This validates the need for comprehensive methods that bring people, process and technology in tandem - expanding TOE theory to AI-specific implementations - giving empirical underpinning to practitioner strategies in emerging market banking contexts where this has been lacking previously (Hamdan et al., 2020; Kitsios et al., 2021).

6. Conclusion

This study revealed that artificial intelligence is an impressive and favourable task in the financing risk reduction in the Saudi banking industry. The findings of 300 banking professionals confirm that AI is highly effective in assessing credit risks, detecting fraud and capital efficiency and delivering very good returns on investment. The supported hypotheses and the findings of the regressions demonstrate the wide effectiveness of Artificial Intelligence to the functions of risk management. Great implementation, however, demands an organisational approach to organisational issues like staff preparedness and quality of data and a management change. Overall, the findings demonstrated the strategic value of AI in the development of risk management and allow further technological progress in the Saudi developing financial context.

7. Limitations

Even though the empirical evidence presented by the study is quite good, it does have a few minor flaws that should be mentioned. Self-reported perceptions formed the basis of the research and do not necessarily represent all the operational facets of the effectiveness of AI, but the sample size is large which helps to address this issue. Cross-sectional survey design provides a glimpse of the current practises, in comparison with the long-term outcomes, although the method is also suitable to establish the existing trends in AI adoption. Moreover, although the sample of the research is comprised of senior Saudi banking practitioners, the comparison of the research sample with the broader region was not included in the study.

Additionally, this study is limited by its focus on a single-country context (Saudi Arabia), which may affect the generalizability of the findings to other institutional and regulatory environments. However, this context-specific focus is intentional, as it allows for a deeper understanding of AI adoption within an emerging economy undergoing rapid digital transformation under Vision 2030. Future research could extend this work through cross-country comparisons to enhance external validity.

8. Future Research Directions

Longitudinal research that may reflect change in actual risk indicators resulting after AI implementation should be included in future research. The performance of single AI models - such as machine learning on credit scoring or anomaly detection - would provide more information about the performance of technologies. The regulatory factors affecting the adoption decision of AI should also be investigated by researchers and the impact of compliance requirements on the adoption approach to AI should also be established. A comparative study of various banking systems of the GCC may indicate cultural, regulatory, and technological variations that influence the results of AI. Lastly, the qualitative studies could provide more information on organisational obstacles and staff willingness and the human-technology interface that will assist in establishing the AI success in financial institutions.

9. References

Al-Matari, E. M., Mgammal, M. H., Alosaimi, M. H., Alruwaili, T. F., & Al-Bogami, S. (2022). Fintech, board of directors and corporate performance in Saudi Arabia financial sector: Empirical study. Sustainability, 14*(17), Article 10750.* https://doi.org/10.3390/su141710750

Ala'raj, M., & Abbod, M. F. (2016). A new hybrid ensemble credit scoring model based on classifiers consensus system approach. Expert Systems with Applications, 64*, 36–55.* https://doi.org/10.1016/j.eswa.2016.07.017

Bank for International Settlements. (2022). Basel III: A global regulatory framework for more resilient banks.

Buchanan, B. G. (2019). Artificial intelligence in finance. *Zenodo.* https://doi.org/10.5281/zenodo.2626454

Cao, L. (2022). AI in finance: Challenges, techniques, and opportunities. ACM Computing Surveys, 55*(3), Article 64.* https://doi.org/10.1145/3502289

Cohen, J. (1988). Statistical power analysis for the behavioral sciences *(2nd ed.). Lawrence Erlbaum Associates.*

George, M. Z. H., Alam, M. K., & Hasan, M. T. (2025). Machine learning for fraud detection in digital banking: A systematic literature review. arXiv. https://arxiv.org/abs/2510.05167

Goodell, J. W., Kumar, S., Lim, W. M., & Pattnaik, D. (2021). Artificial intelligence and machine learning in finance: Identifying foundations, themes, and research clusters from bibliometric analysis. Journal of Behavioral and Experimental Finance, 32*, Article 100577.* https://doi.org/10.1016/j.jbef.2021.100577

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). Multivariate data analysis *(8th ed.). Cengage Learning.*

Hamdan, A., Khamis, R., Al Hawaj, A., & Barone, E. (2020). Artificial intelligence in banking: Evidence from Bahrain. Journal of Electronic Commerce in Organizations, 18*(2), 1–14.*

Jain, A., Kulkarni, R., & Lin, S. (2025). Explainable AI in big data fraud detection. arXiv. https://arxiv.org/abs/2512.16037

Khandani, A. E., Kim, A. J., & Lo, A. W. (2010). Consumer credit-risk models via machine-learning algorithms. Journal of Banking & Finance, 34*(11), 2767–2787.*

Kitsios, F., Giatsidis, I., & Kamariotou, M. (2021). Digital transformation and strategy in the banking sector: Evaluating the acceptance rate of e-services. Journal of Open Innovation: Technology, Market, and Complexity, 7*(3), Article 204.* https://doi.org/10.3390/joitmc7030204

Kumar, A. (2024). Redefining finance: The influence of artificial intelligence (AI) and machine learning (ML). arXiv. https://arxiv.org/abs/2410.15951

Leo, M., Sharma, S., & Maddulety, K. (2019). Machine learning in banking risk management: A literature review. Risks, 7*(1), Article 29.*

Mediana, A. M., & Sandari, T. E. (2024). Implementation of artificial intelligence in fraud detection and prevention in internal audit: Case study in the banking sector. International Journal of Economics, Social Science, Entrepreneurship and Management, 4*(2), 155–167. https://doi.org/10.62951/ijessm.v4i2.532*

Ngai, E. W. T., Hu, Y., Wong, Y. H., Chen, Y., & Sun, X. (2011). The application of data mining techniques in financial fraud detection. Decision Support Systems, 50*(3), 559–569.*

Nunnally, J. C., & Bernstein, I. H. (1994). Psychometric theory *(3rd ed.). McGraw-Hill.*

Nuruzzaman, N., Weber, J., & Miah, S. J. (2020). Regulating artificial intelligence: Saudi Arabia and the Gulf states. Policy and Society, 39*(4), 530–546.*

Rahim, A., Jan, S. U., Ali, S., Shah, D., & Tahir, M. (2026). AI-driven financial fraud detection in Pakistan's banking sector: Bridging strategic intent and operational implementation. Humanities and Social Sciences Communications, 13*, Article 606. https://doi.org/10.1057/s41599-026-07406-6*

Saudi Central Bank. (2023). Annual report 2023.

Tornatzky, L. G., & Fleischer, M. (1990). The processes of technological innovation*. Lexington Books*.

West, J., & Bhattacharya, M. (2016). Intelligent financial fraud detection: A comprehensive review. Computers & Security, 57*, 47–66.*

Yang, H., Shukur, Z., & Sahran, S. (2026). A review of artificial intelligence for financial fraud detection. Applied Sciences, 16*(4), Article 1931. https://doi.org/10.3390/app16041931*

Yaseen, H., & Al-Amarneh, A. (2025). Adoption of artificial intelligence-driven fraud detection in banking: The role of trust, transparency, and fairness perception in financial institutions in the United Arab Emirates and Qatar. Journal of Risk and Financial Management, 18*(4), Article 217.* https://doi.org/10.3390/jrfm18040217