“Artificial intelligence-driven predictive analytics and institutional performance in Gulf financial systems: Evidence from GCC financial institutions”

AUTHORS	Amer Morshed Laith T. Khrais

ARTICLE INFO	Amer Morshed and Laith T. Khrais (2026). Artificial intelligence-driven predictive analytics and institutional performance in Gulf financial systems: Evidence from GCC financial institutions. *Banks and Bank Systems*, *21*(1), 31-46. doi: 10.21511/bbs.21(1).2026.03
DOI	http://dx.doi.org/10.21511/bbs.21(1).2026.03
RELEASED ON	Tuesday, 27 January 2026
RECEIVED ON	Monday, 13 October 2025
ACCEPTED ON	Wednesday, 17 December 2025

JOURNAL	"Banks and Bank Systems"
ISSN PRINT	1816-7403
ISSN ONLINE	1991-7074
PUBLISHER	LLC “Consulting Publishing Company “Business Perspectives”
FOUNDER	LLC “Consulting Publishing Company “Business Perspectives”

NUMBER OF REFERENCES	NUMBER OF FIGURES	NUMBER OF TABLES
62	1	16

BUSINESS PERSPECTIVES

LLC "CPC "Business Perspectives"
Hryhorii Skovoroda lane, 10,
Sumy, 40022, Ukraine

www.businessperspectives.org

Amer Morshed (Jordan), **Laith Khrais** (Jordan)

ARTIFICIAL INTELLIGENCE-DRIVEN PREDICTIVE ANALYTICS AND INSTITUTIONAL PERFORMANCE IN GULF FINANCIAL SYSTEMS: EVIDENCE FROM GCC FINANCIAL INSTITUTIONS

Abstract

The integration of artificial intelligence-driven predictive analytics has redefined financial management and decision-making across Gulf economies. This study compares the performance of artificial-intelligence-based and traditional predictive models using data from twenty financial institutions from six Gulf Cooperation Council countries. A quantitative cross-sectional design was adopted, and analysis of variance revealed statistically significant differences ($p < 0.001$) across all indicators. Predictive accuracy increased from 83.5 to 91.5 per cent ($F = 4.23 \times 10^{29}$), operational efficiency from 12 to 19.5 per cent ($F = 1.31 \times 10^{31}$), risk-management effectiveness from 7.0 to 9.3 points ($F = 2.69 \times 10^{30}$), and customer satisfaction from 6.5 to 8.5 points ($F = 1.69 \times 10^{30}$). Regression analyses confirmed these outcomes: model type produced significant coefficients for predictive accuracy ($\beta = 8.21$, $p < 0.001$), operational efficiency ($\beta = 7.46$, $p < 0.001$), risk-management effectiveness ($\beta = 2.29$, $p < 0.001$), and customer satisfaction ($\beta = 1.84$, $p < 0.001$). The overall model explained 84 per cent ($R^2 = 0.84$) of the variation in institutional performance, confirming the strong predictive power of artificial-intelligence models. These results demonstrate that intelligent predictive systems significantly enhance accuracy, efficiency, and stakeholder value. The study concludes that transparent and ethically governed analytical frameworks are essential for sustainable financial competitiveness and responsible innovation in the Gulf region.

Keywords artificial intelligence, predictive analytics, institutional performance, operational efficiency, risk management, customer satisfaction, Gulf financial sector

JEL Classification G21, O33, C38

Type of the article: Research Article

Received on: 13th of October, 2025
Accepted on: 17th of December, 2025
Published on: 27th of January, 2026

Amer Morshed, Ph.D., Assistant Professor, Faculty of Business, Department of Accounting, Al-Zaytoonah University of Jordan, Jordan. (Corresponding author)

Laith Khrais, Ph.D., Assistant Professor, Faculty of Business, Department of Business, Middle East University, Jordan.

Conflict of interest statement:
Author(s) reported no conflict of interest

INTRODUCTION

The integration of Artificial Intelligence (AI) and predictive analytics has become a cornerstone of financial transformation, redefining how institutions analyze risks, manage portfolios, and forecast market behavior. Across global financial systems, AI tools are increasingly embedded in decision-support processes to enhance precision and operational efficiency. These technologies enable dynamic learning from large and unstructured data, producing more reliable forecasts and strengthening risk mitigation frameworks. Within the Gulf Cooperation Council (GCC), the adoption of predictive analytics represents both a technological and strategic shift, as financial institutions seek to balance innovation with regulation and ethical accountability.

Despite the recognized potential of AI, empirical evidence from Arab Gulf financial institutions remains limited. Prior research has predominantly focused on Western or East-Asian markets, leaving the

regional context underexplored in terms of institutional readiness, model transparency, and cultural acceptance of automation. Moreover, comparative studies contrasting AI-driven predictive models with traditional statistical techniques in GCC finance are scarce. This absence of localized evidence restricts policymakers and industry leaders from understanding how AI adoption affects accuracy, efficiency, and customer satisfaction within regulated financial environments.

Accordingly, this study aims to examine and compare the performance of AI-driven and traditional predictive models across financial institutions in the GCC. Building on the Technology Acceptance Model, Diffusion of Innovation, and Unified Theory of Acceptance and Use of Technology, it evaluates how these technologies influence predictive accuracy, operational efficiency, risk management, and customer satisfaction.

Theoretically, the study contributes to the growing discourse on digital transformation in emerging economies by integrating predictive analytics within institutional and behavioral frameworks. Practically, it provides actionable insights for managers and regulators to harness AI responsibly while ensuring transparency and effective governance.

1. LITERATURE REVIEW AND HYPOTHESES

The financial sector of the Gulf Cooperation Council (GCC) is undergoing a profound digital transformation, largely driven by the integration of artificial intelligence (AI) and predictive analytics. These technologies have redefined decision-making processes, enabling financial institutions to forecast outcomes with greater precision, optimize service delivery, and mitigate risks associated with market volatility. The strategic application of predictive analytics and AI allows banks and other financial entities to process massive datasets, identify emerging trends, and make timely, evidence-based decisions (Gofman & Jin, 2024; Sathupadi et al., 2025). Across GCC economies, AI tools are increasingly utilized to improve credit risk evaluation, detect fraudulent activity, and personalize customer interactions. Empirical research highlights that AI models offer superior accuracy in credit scoring and fraud detection compared to traditional systems, due to their self-learning capabilities and continuous improvement mechanisms (Ali et al., 2024; Morshed & Khrais, 2025). The deployment of Bahrain Bank ABC's "Fatema" initiative exemplifies how AI-powered customer service platforms enhance communication efficiency while minimizing operational costs.

In addition to improving performance, AI technologies reinforce compliance through enhanced *Know-Your-Customer* (KYC) and *Anti-Money Laundering* (AML) processes (Conway & Rasool, 2025; Horobets et al., 2025). Their capacity to analyze structured and unstructured data helps financial institutions to detect suspicious transactions and maintain adherence to international reporting standards (Kurum, 2023; Morshed, 2025b). The theoretical foundations for understanding AI adoption in finance are rooted in established frameworks such as the Technology Acceptance Model (TAM), Diffusion of Innovation (DoI), and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Abraham et al., 2022; Almahri & Saleh, 2025). These models explain how perceived usefulness, performance expectancy, and institutional readiness influence technological adoption (Alshehadeh et al., 2023). Within the GCC, adoption is moderated by regulatory conservatism, limited algorithmic transparency, and public perceptions of automation. Although AI applications offer significant efficiency gains, challenges persist regarding bias mitigation, data quality, and model interpretability. Smith and Lamprecht (2024) and Salhab et al. (2025) emphasize that algorithmic credibility depends on tuning processes that enhance transparency and minimize systemic bias. AI's dependence on high-quality infrastructure and ethical frameworks also constrains large-scale integration. For AI and predictive analytics to reach full maturity, future research must focus on improving transparency, establishing unified governance standards, and ensuring compliance with regional regulatory frameworks (Kocaoglu & Kirmizi, 2025; Sampat et al., 2024).

http://dx.doi.org/10.21511/bbs.21(1).2026.03

Empirical work from emerging economies supports the importance of cultural and institutional context in shaping AI adoption. Morshed (2024a) and Ben Abdallah and Bahloul (2025) found that regulatory and ethical dimensions strongly influence technology adoption in MENASA financial institutions. Similarly, Adeoye et al. (2024) demonstrated that AI-driven credit models improved SME financing performance in Nigeria while confirming that trust and digital literacy remain decisive adoption factors (Shaban & Omoush, 2025). These insights align with Abraham et al. (2022), who observed that predictive analytics supports improved decision-making across multiple sectors by providing data-driven frameworks. Collectively, these findings reinforce that AI's success depends not only on technological advancement but also on contextual alignment with local governance and cultural expectations.

A parallel stream of literature compares classical statistical forecasting techniques with emerging AI-based predictive systems. Traditional methods, such as regression analysis, time-series modeling, and scenario planning, have long been valued for their interpretability, regulatory compatibility, and methodological transparency (Denwood et al., 2023; Morshed, 2024b). These models are easily auditable and allow for clear traceability of decisions, an aspect vital to maintaining public trust in regulated financial markets (Al-Muntasir, 2022). Nonetheless, such models struggle to handle the scale and heterogeneity of financial data generated in the digital era. The exponential growth in data volume, velocity, and variety demands adaptive tools capable of uncovering nonlinear and hidden relationships (Kumar et al., 2024; Shakir et al., 2025). AI-based systems, through machine learning and deep learning techniques, address these limitations by recognizing complex interactions and adjusting to market fluctuations. They deliver superior forecasting precision and responsiveness to economic shocks (Elahi et al., 2023; Moro-Visconti et al., 2023).

Despite these advantages, the literature identifies major concerns. The most significant is the "black-box" problem, which refers to the opacity of AI models and the inability of users to fully understand the decision-making process (Director, 2025; Şahin et al., 2025). This lack of transparency raises challenges for auditability and accountability, particularly in high-stakes environments like banking, where explainability is a regulatory requirement. Furthermore, data bias presents another challenge. If the training data used in AI systems is incomplete or unbalanced, the resulting models may produce skewed or discriminatory outputs. Díaz-Rodríguez et al. (2023) highlight that data privacy, fairness, and informed consent are ethical dimensions that must accompany algorithmic design (Taqa, 2025). Consequently, scholars call for explainable AI frameworks that preserve both interpretability and efficiency, ensuring accountability and fairness in financial decision-making. Balancing model transparency with analytical sophistication remains an essential research frontier for predictive finance in the GCC and beyond (Al-Daoud & Abu-AlSondos, 2025).

AI and predictive analytics are also recognized for their ability to improve efficiency, cost-effectiveness, and customer relationship management. The automation of data-intensive tasks enhances productivity and reduces manual errors, enabling institutions to focus on strategic priorities (Mogaji & Nguyen, 2022; Schmitt, 2023). Risk management, a core banking function, benefits significantly from AI integration. Predictive analytics enables proactive risk assessment, allowing institutions to identify potential losses before they occur and to strengthen their resilience against financial shocks (Nair et al., 2024; Morshed, 2024c). Moreover, AI transforms customer engagement strategies. Through advanced segmentation and behavioral analysis, institutions can predict consumer needs, tailor financial products, and design personalized marketing strategies (Kasem et al., 2024; Koskelainen et al., 2023). Such personalization not only enhances satisfaction but also fosters long-term loyalty. Nevertheless, scholars warn that innovation must align with ethical standards. Burr and Leslie (2023) and Morshed (2025a) underline the necessity of fairness and transparency in AI deployment, calling for robust ethical governance frameworks that balance innovation with social responsibility. Thus, AI's contribution to operational and customer value creation must be weighed against moral, regulatory, and security concerns (Nastoska et al., 2025).

While optimism dominates much of the literature, numerous studies raise cautionary notes about the risks and unintended consequences of

AI in finance. The opacity of machine-learning systems remains a persistent problem, as many models still operate as incomprehensible "black boxes" (Brożek et al., 2023; Hassija et al., 2024). This lack of explainability complicates the verification of outcomes and threatens accountability in decision-making. Data integrity and bias further constrain AI's reliability. Poor-quality or incomplete data may lead to erroneous predictions with far-reaching financial implications (Ooi et al., 2023; Roshanaei, 2024). The growing dependence on personal and financial data also introduces privacy and data protection risks. Berman et al. (2024) stress that responsible AI requires maintaining confidentiality and protecting individuals' consent rights. Mühlhoff (2023) warns that existing laws and regulatory frameworks remain insufficient to address these emerging challenges, widening the gap between innovation and oversight. Consequently, a dual narrative persists in the academic discourse – one celebrating AI's capacity to improve efficiency and innovation (Alsaghir, 2023) and another emphasizing the ethical risks associated with automation. This tension highlights the urgent need for flexible, adaptive regulation that ensures technological advancement does not compromise transparency and accountability in financial institutions (Oreqat, 2021).

Taken together, the reviewed literature identifies clear gaps in both theory and practice. Although extensive conceptual work exists, there remains a shortage of empirical research directly comparing AI-based predictive analytics with traditional financial modeling methods in realistic banking environments. Most studies rely on theoretical discussions or isolated case analyses without robust quantitative validation. Furthermore, limited attention has been given to the regulatory and ethical dimensions of AI adoption in the GCC, where financial ecosystems are characterized by strict oversight and emerging digital transformation policies. Addressing these research gaps is vital for understanding how AI-based predictive models outperform conventional methods and how institutions can leverage such technologies within ethical and regulatory constraints.

Therefore, this study aims to evaluate the comparative impact of AI-driven predictive analytics on forecasting accuracy, operational efficiency, risk management, and customer engagement in GCC financial institutions. The following hypotheses are proposed based on the insights derived from the literature:

H1: AI-driven predictive analytics demonstrate higher predictive accuracy than traditional financial models.

H2: The adoption of AI-driven analytics significantly enhances operational efficiency in financial institutions.

H3: AI-driven analytics improve risk-management capabilities more effectively than traditional approaches.

H4: AI-driven analytics generate deeper customer insights, enhancing satisfaction and retention.

2. METHODS

This study adopted a quantitative cross-sectional design to evaluate the comparative performance of artificial-intelligence (AI)-driven and traditional predictive models within financial institutions across the Gulf Cooperation Council (GCC). The aim was to provide empirical evidence on how predictive analytics approaches influence institutional performance metrics and support data-driven decision-making and policy formulation. Following the conventions of quantitative research in finance and technology adoption (Khattak et al., 2023), the design combined survey-based perception data with secondary financial indicators to obtain both subjective and objective measures of predictive model effectiveness.

The population comprised financial institutions operating in the Arab Gulf region, including commercial banks, insurance companies, investment houses, and financial-technology firms. A purposive sampling method was employed to ensure sectoral and geographical coverage. The final sample included 20 institutions from six GCC countries – the United Arab Emirates, Saudi Arabia, Bahrain, Kuwait, Qatar, and Oman. Institutions were selected according to active implementation of predictive technologies in areas such as credit-

http://dx.doi.org/10.21511/bbs.21(1).2026.03

risk modeling, fraud detection, and customer analytics. Because AI adoption remains limited in the region, the sample was considered representative of early adopters. In total, 152 decision-makers participated, typically between five and ten respondents per institution, representing managerial and analytical roles.

A structured questionnaire was designed to measure perceptions of model effectiveness across four performance domains: predictive accuracy, operational efficiency, risk-management effectiveness, and customer satisfaction. The instrument consisted of 30 items rated on a five-point Likert scale ranging from "strongly disagree" (1) to "strongly agree" (5). Each construct was operationalized following established measures in financial analytics literature, including predictive accuracy, operational efficiency, risk-management effectiveness, and customer satisfaction (Mamakou et al., 2024). The questionnaire was pre-tested with three institutions to ensure clarity and contextual relevance. Reliability analysis confirmed internal consistency, with Cronbach's alpha values above 0.80 across all constructs, exceeding recommended thresholds for social-science research.

A detailed overview of the sampled institutions included in the study is provided in Appendix Table 1, which summarizes their distribution across countries and financial sectors. This breakdown supports the representativeness of the sample and clarifies the institutional coverage of the analysis.

Primary data were complemented by five years of secondary financial information obtained from institutional reports and Bloomberg databases. These data included operational costs, revenues, profit margins, and macro-level indicators such as interest-rate trends and market indices, providing an objective baseline for comparing AI-based and traditional prediction models.

The independent variable was the type of predictive model (AI-driven = 1, traditional = 0). Dependent variables represented institutional outcomes: predictive accuracy, operational efficiency, risk-management effectiveness, and customer satisfaction. Three control variables were included – institution size (Hasan & Lu, 2023), market conditions, and regulatory environment (Ahmad et al., 2023) – to isolate the effect of predictive-model type from contextual influences.

Data were analyzed using IBM SPSS Statistics 27. Descriptive statistics summarized the characteristics of institutions and constructs. ANOVA was employed to examine mean differences across model types, and multivariate regression assessed the effect of predictive-model type on institutional outcomes while controlling for size, market, and regulatory factors (Guo et al., 2023). Model adequacy was evaluated using R-squared, adjusted R-squared, F-statistic, mean-squared error (MSE), root-mean-squared error (RMSE), and information-criterion measures, such as AIC and BIC, to ensure parsimonious yet robust specification. Detailed numerical outputs appear in the Results section.

Ethical approval for this research was obtained from Al-Zaytoonah University of Jordan (ZUJ-BUS-2025-Feb-ETHICS-1213). Participation was voluntary, informed consent was secured from all respondents, and confidentiality of institutional and individual data was maintained in accordance with academic-ethics standards.

All input data used in this study have been deposited in an open-access Zenodo repository to ensure transparency and reproducibility (https://doi.org/10.5281/zenodo.18363032). The dataset is

Table 1. Distribution of sampled institutions by country and sector

Country	Banks	Insurance	Fintech	Investment	Total
United Arab Emirates	3	1	1	–	5
Saudi Arabia	2	1	1	–	4
Bahrain	1	1	1	–	3
Kuwait	1	1	1	–	3
Qatar	2	1	–	–	3
Oman	1	–	1	–	2
Total	10	5	5	–	20

original and was generated specifically for this research; it has not been used in any prior publications. Making the data publicly available supports verification, facilitates future research, and aligns with open-science standards. In addition, the full questionnaire instrument used for primary data collection is provided in the Appendix to support clarity, replicability, and methodological transparency.

3. RESULTS

Descriptive and inferential analyses were conducted to assess the comparative effectiveness of AI-driven and traditional predictive models in GCC financial institutions. The empirical results confirm that AI adoption produces consistent improvements in predictive accuracy, operational efficiency, risk-management effectiveness, and customer satisfaction.

The descriptive statistics summarized in Table 2 shows that institutions employing AI-driven models consistently outperform those relying on traditional techniques. Mean predictive accuracy reached 91.5% for AI models versus 83.5 % for traditional ones, while operational efficiency rose from 12% to 19.5%. Risk-management and customer-satisfaction scores were likewise higher for AI adopters, confirming that algorithmic analytics enhance both financial and service performance (Ramzani et al., 2024).

Model-fit statistics in Table 3 confirm robustness: $R^2 = 84.09\%$, Adjusted $R^2 = 83.87\%$, $F = 389.7$, with low MSE and RMSE values. The AIC and BIC indices demonstrate strong explanatory capacity and parsimony, validating the reliability of the model specification.

Table 3. Model-fit indicators for multivariate regression analysis

Measure	Value	Interpretation
R-squared (R^2)	84.09%	Explains 84.09% of variance
Adjusted R^2	83.87%	Adjusted for predictors
F-statistic	389.7	Model significance
MSE	2.88	Average squared error
RMSE	1.7	Root mean squared error
AIC	1178.3	Model quality
BIC	1196.8	Model quality with penalty

ANOVA results presented in Tables 4-7 confirm statistically significant mean differences between AI-driven and traditional predictive models across all examined dimensions ($p < 0.001$). These findings collectively verify that the type of predictive model substantially affects institutional performance outcomes in GCC financial institutions.

For predictive accuracy, the exceptionally high F-statistic in Table 4 demonstrates that AI-based models deliver markedly greater forecasting precision. This superiority stems from their ability to detect complex, nonlinear interactions among financial variables that conventional statistical approaches often overlook, resulting in more reliable outcome estimation (Vancsura et al., 2025).

Table 2. Descriptive statistics of key study variables

Variable Description	Type of Data	Group	Mean	Median	S.D	Range	N
Predictive Accuracy (%)	Dependent	AI-driven	91.5	92	1.5	88-95	152
		Traditional	83.5	84	2	80-87	152
Operational Efficiency (%)	Dependent	AI-driven	19.5	19	1	17-22	152
		Traditional	12	12	1	10-14	152
Risk-Management Effectiveness (Score)	Dependent	AI-driven	9.3	9	0.5	8-10	152
		Traditional	7	7	0.8	6-8	152
Customer Satisfaction (Score)	Dependent	AI-driven	8.5	9	0.5	8-9	152
		Traditional	6.5	7	0.5	6-7	152
Institution Size (Total Assets USD B)	Control	AI-driven	55	55	10	35-75	152
		Traditional	45	45	10	35-55	152
Market Conditions (Index)	Control	AI-driven	5.8	5.8	0.2	5.4-6.2	152
		Traditional	5.2	5.2	0.2	4.8-5.6	152
Regulatory Environment (Score)	Control	AI-driven	8.9	9	0.3	8.3-9.5	152
		Traditional	8.1	8	0.3	7.5-8.7	152

http://dx.doi.org/10.21511/bbs.21(1).2026.03

Table 4. ANOVA – Predictive accuracy

Source	Sum of Squares	df	F-statistic	p-value
Model Type	4 864.00	1	4.23×10^{29}	0
Residual	≈ 0	302	–	–

Table 5. ANOVA – Operational efficiency

Source	Sum of Squares	df	F-statistic	p-value
Model Type	4 275.00	1	1.31×10^{31}	0
Residual	≈ 0	302	–	–

Table 6. ANOVA – Risk-management effectiveness

Source	Sum of Squares	df	F-statistic	p-value
Model Type	402.04	1	2.69×10^{30}	0
Residual	≈ 0	302	–	–

Table 7. ANOVA – Customer satisfaction

Source	Sum of Squares	df	F-statistic	p-value
Model Type	304.00	1	1.69×10^{30}	0
Residual	≈ 0	302	–	–

Operational efficiency also shows a significant improvement in Table 5, confirming that AI integration streamlines workflows and automates repetitive data tasks. Such automation reduces operational costs, accelerates analytical processing, and minimizes human error – benefits consistent with prior empirical observations that AI enhances productivity through self-optimizing algorithms.

In terms of risk-management effectiveness, Table 6 indicates that institutions using AI achieve superior results in identifying and mitigating potential risks. Intelligent systems continuously analyze large and dynamic data flows, enabling earlier detection of anomalies and emergent financial threats that might remain unnoticed under traditional frameworks.

Finally, customer satisfaction also increases significantly, as reported in Table 7. The improvement reflects the capacity of AI-driven models to provide personalized, timely, and adaptive services

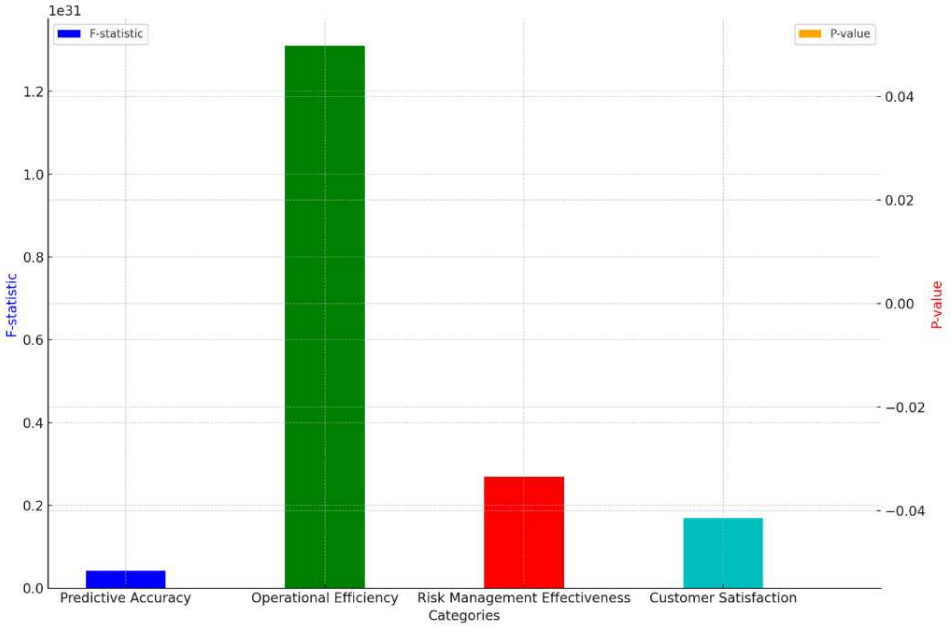

Figure 1. ANOVA summary of performance effects

that align closely with customer needs and behavioral patterns. These results collectively affirm that AI not only improves technical precision and internal efficiency but also strengthens client relationships and institutional resilience across the GCC financial sector.

Regression analyses reported in Tables 8-11 quantify the influence of predictive-model type on institutional performance while controlling for organization size, market conditions, and regulatory environment. The results show a consistent and statistically significant advantage of AI-driven models across all outcome variables, confirming their robustness and broad applicability in the GCC financial context.

For predictive accuracy, the model-type coefficient ($\beta = 8.209$, $p < 0.001$) indicates an improvement of roughly 8 %. This confirms that AI algorithms extract complex, nonlinear patterns that traditional techniques cannot capture, producing more reliable forecasts. The insignificance of control variables suggests that this advantage holds across institutions of varying size and regulatory intensity (Mennella et al., 2024).

Regarding operational efficiency, the coefficient ($\beta = 7.457$, $p < 0.001$) reveals a 7.46 % performance gain. The finding reflects process automation and faster data handling that shorten decision cycles and reduce manual errors. Efficiency benefits appear uniform across different institutional scales, consistent with evidence that self-learning systems enhance productivity regardless of size (Patrício et al., 2025).

For risk-management effectiveness, the positive coefficient ($\beta = 2.289$, $p < 0.001$) demonstrates that AI facilitates proactive risk detection through

Table 8. Predictive accuracy model summary

Variable	Coefficient	Std. Error	t-value	p-value
Constant	85.454	3.882	22.013	< 0.001
Model Type	8.209	0.467	17.561	< 0.001
Institution Size	– 0.001	0.009	– 0.119	0.905
Market Conditions	– 0.128	0.531	– 0.240	0.811
Regulatory Environment	– 0.130	0.335	– 0.388	0.698

Table 9. Operational efficiency model summary

Variable	Coefficient	Std. Error	t-value	p-value
Constant	11.547	0.886	13.034	< 0.001
Model Type	7.457	0.106	70.291	< 0.001
Institution Size	– 0.012	0.020	– 0.626	0.532
Market Conditions	– 0.228	0.121	– 1.884	0.061
Regulatory Environment	0.320	0.076	4.214	< 0.001

Table 10. Risk-management effectiveness model summary

Variable	Coefficient	Std. Error	t-value	p-value
Constant	6.107	1.213	5.036	< 0.001
Model Type	2.289	0.140	16.330	< 0.001
Institution Size	– 0.004	0.010	– 0.420	0.675
Market Conditions	– 0.139	0.162	– 0.860	0.391
Regulatory Environment	0.228	0.099	2.300	0.022

Table 11. Customer satisfaction model summary

Variable	Coefficient	Std. Error	t-value	p-value
Constant	5.884	1.173	5.015	< 0.001
Model Type	1.838	0.141	13.008	< 0.001
Institution Size	– 0.003	0.003	– 0.905	0.366
Market Conditions	– 0.048	0.161	– 0.301	0.764
Regulatory Environment	0.124	0.101	1.219	0.224

http://dx.doi.org/10.21511/bbs.21(1).2026.03

high-volume, real-time analysis. The regulatory-environment variable ($\beta = 0.228$, $p = 0.022$) is also significant, implying that stronger governance frameworks magnify AI's risk-control benefits (Bader et al., 2025).

Finally, customer satisfaction improves by 1.838 points ($p < 0.001$), confirming that AI-based analytics personalize services and increase responsiveness (Marti et al., 2024). None of the remaining control factors is significant, showing that customer-experience gains stem primarily from technological capability rather than institutional context.

Overall, the regression outcomes corroborate the ANOVA findings: AI-driven predictive analytics consistently enhance forecasting accuracy, operational performance, risk oversight, and client satisfaction across GCC financial institutions.

Overall, the empirical findings clearly establish that AI-driven predictive analytics significantly outperform traditional models in every examined dimension. The results substantiate all proposed hypotheses and demonstrate that algorithmic intelligence enhances financial accuracy, operational efficiency, risk mitigation, and customer value creation within GCC financial institutions. High explanatory power and consistent significance levels across models underscore the reliability of these results and their relevance for strategic technology adoption.

The results demonstrate that AI adoption significantly improves predictive accuracy, operational efficiency, risk-management effectiveness, and customer satisfaction. These findings confirm all proposed hypotheses (H1-H4) and reinforce the theoretical assumption that advanced technologies, when aligned with institutional conditions, generate measurable performance advantages

4. DISCUSSION

This study investigated whether AI-driven predictive analytics outperform traditional financial models within GCC financial institutions.

The superior predictive accuracy of AI-based models highlights their ability to capture complex, nonlinear patterns and rapidly adapt to dynamic financial environments – capabilities that traditional models lack. This evidence supports the Technology Acceptance Model (TAM) and Diffusion of Innovation (DoI) frameworks, which emphasize performance expectancy and perceived usefulness as central to adoption (Abraham et al., 2022). The results also mirror Ramzani et al. (2024), who found that AI enhances forecasting reliability in banking operations. By demonstrating consistent accuracy improvements across institutions, the study confirms that perceived usefulness translates into tangible forecasting and decision-making benefits.

The improvement in operational efficiency further illustrates AI's transformative role. A 7.46 % increase in efficiency reflects the automation of data processing and the reduction of manual intervention. These findings correspond with Alsmadi and Alrawashdeh (2025), who noted that automation streamlines financial workflows and minimizes errors. From a resource-based-view perspective, AI constitutes an organizational capability that converts data resources into operational gains. The non-significance of institution size implies scalability, meaning both large and mid-sized institutions benefit equally from predictive automation.

In risk management, AI's analytical depth provides institutions with proactive risk identification and mitigation capabilities. The significant coefficient for the regulatory environment ($\beta = 0.228$, $p = 0.022$) demonstrates that strong governance frameworks enhance AI's effectiveness (Alshehadeh et al., 2025). This supports the Unified Theory of Acceptance and Use of Technology (UTAUT), which identifies facilitating conditions – such as regulation and ethics – as key to sustained technology utilization (Mennella et al., 2024). The result also underscores that regulation does not constrain innovation; rather, it strengthens institutional trust and algorithmic accountability when appropriately structured.

The findings related to customer satisfaction confirm that AI improves service personalization and response timeliness. AI-enabled systems allow financial institutions to anticipate customer needs and deliver adaptive services, strengthening engagement and retention (Marti et al., 2024;

Morshed et al., 2024). The absence of significant market or institutional effects indicates that satisfaction gains arise mainly from technology rather than context, reflecting AI's potential to standardize high-quality customer experiences across diverse financial environments.

Taken together, the results demonstrate that AI integration enhances performance across technical, operational, and relational dimensions. Theoretically, this extends TAM and DoI by verifying that perceived usefulness and innovation compatibility translate into measurable institutional performance. Practically, the study emphasizes that AI adoption should be accompanied by robust ethical and regulatory frameworks to sustain transparency and fairness (Burr & Leslie, 2023). GCC regulators are encouraged to expand innovation sandboxes and AI governance mechanisms, while financial managers should invest in explainable, auditable systems that align automation with compliance.

Although the findings are robust, the study's cross-sectional design limits causal inference, and the purposive sample may not fully capture sectoral diversity. Future research should employ longitudinal and comparative designs to explore the evolution of AI adoption and its interaction with changing policy environments. Overall, this study confirms that AI-driven predictive analytics serve as a catalyst for sustainable financial transformation in the GCC, balancing technological innovation with accountability and institutional trust.

CONCLUSION

This study examined the comparative impact of AI-driven and traditional predictive models on institutional performance within Gulf Cooperation Council financial institutions. The empirical analysis confirmed that AI adoption substantially enhances predictive accuracy, operational efficiency, risk-management effectiveness, and customer satisfaction, offering a comprehensive picture of its transformative role in regional finance.

Theoretically, the findings extend the Technology Acceptance Model, Diffusion of Innovation, and Unified Theory of Acceptance and Use of Technology by demonstrating that perceived usefulness and facilitating conditions translate into measurable organizational outcomes. AI's adaptability and learning capacity allow financial institutions to move beyond descriptive analytics toward proactive, data-driven decision-making.

From a practical standpoint, financial managers are encouraged to invest in explainable AI systems that integrate transparency, fairness, and accountability. Regulators in GCC countries should continue developing innovation sandboxes and AI-ethics frameworks to ensure that technological advancement aligns with compliance and public trust. The combination of robust governance and responsible innovation can maximize the efficiency gains revealed in this study while mitigating algorithmic and ethical risks.

Although limited by its cross-sectional design and purposive sampling, this research provides a strong empirical basis for future longitudinal and comparative investigations. Overall, the study demonstrates that AI-based predictive analytics constitute a strategic asset for building sustainable, resilient, and customer-centric financial institutions in the Gulf region.

AUTHOR CONTRIBUTIONS

Conceptualization: Amer Morshed, Laith Khrais.
Data curation: Amer Morshed, Laith Khrais.
Formal analysis: Amer Morshed.
Funding acquisition: Amer Morshed.
Investigation: Amer Morshed.

http://dx.doi.org/10.21511/bbs.21(1).2026.03

Methodology: Amer Morshed, Laith Khrais.
Resources: Amer Morshed.
Software: Amer Morshed.
Validation: Amer Morshed.
Visualization: Amer Morshed.
Writing – original draft: Amer Morshed.
Writing – reviewing & editing: Laith Khrais.

REFERENCES

1. Abraham, R., Samad, M. E., Bakhach, A. M., El-Chaarani, H., Sardouk, A., Nemar, S. E., & Jaber, D. (2022). Forecasting a stock trend using genetic algorithm and random forest. *Journal of Risk and Financial Management, 15*(5), 188. https://doi.org/10.3390/jrfm15050188
2. Adeoye, O. B., Okoye, C. C., Ofodile, O. C., Odeyemi, O., Addy, W. A., & Ajayi-Nifise, A. O. (2024). Integrating artificial intelligence in personalized insurance products: A pathway to enhanced customer engagement. *International Journal of Management & Entrepreneurship Research, 6*(3), 502-511. https://doi.org/10.51594/ijmer.v6i3.840
3. Ahmad, A. K., Nahar, H. M., & Manajreh, M. M. N. (2023). Effect of social media on shaping the agenda of the communicator in the Jordanian TV channels. *Middle East Journal of Communication Studies, 3*(2), Article 3. (In Arabic). https://doi.org/10.71220/2585-003-002-003
4. Al-Daoud, K. I., & Abu-AlSondos, I. A. (2025). Robust AI for financial fraud detection in the GCC: A hybrid framework for imbalance, drift, and adversarial threats. *Journal of Theoretical and Applied Electronic Commerce Research, 20*(2), 121. https://doi.org/10.3390/jtaer20020121
5. Ali, S. A., Al-Absy, M. S. M., Al Astal, A. Y. M., & Gharaibeh, A. M. O. (2024). Impact of financial technology on future of banking in Bahrain: Opportunities and challenges. In *Digital technology and changing roles in managerial and financial accounting: Theoretical knowledge and practical application* (Vol. 36, pp. 141-153). https://doi.org/10.1108/S1479-351220240000036014
6. Almahri, F. A. A. J., & Saleh, N. I. M. (2025). Insights into technology acceptance: A concise review of key theories and models. In Al Mubarak, M., & Hamdan, A. (Eds.), *Innovative and intelligent digital technologies: Towards an increased efficiency* (Vol. 569, pp. 797-807). https://doi.org/10.1007/978-3-031-71649-2_67
7. Al-Muntasir, M. (2022). The phenomenon of information flow from traditional and new media about the Corona pandemic from the perspective of newly graduated media professionals in Yemen. *Middle East Journal of Communication Studies, 2*(2), Article 1. (In Arabic). https://doi.org/10.71220/2585-002-002-005
8. Alsaghir, M. (2023). Digital risks and Islamic FinTech: A road map to social justice and financial inclusion. *Journal of Islamic Accounting and Business Research, 16*(7), 1265-1282. https://doi.org/10.1108/JIABR-10-2022-0262
9. Alshehadeh, A. R., Abu Nahleh, I. T., & Al-Zyoud, I. A. (2025). The impact of financial and non-financial information on investment decision-making in the Jordanian business environment. *Al-Zaytoonah Journal of Business, 1*(1), 1-8. Retrieved from https://journals.zuj.edu.jo/zjjb/Published-Papers/2025.1.10.pdf
10. Alshehadeh, A., Elrefae, G., Belarbi, A., Qasim, A., & Al-Khawaja, H. (2023). The impact of business intelligence tools on sustaining financial report quality in Jordanian commercial banks. *Uncertain Supply Chain Management, 11*(4), 1667-1676. https://doi.org/10.5267/j.uscm.2023.7.002
11. Alsmadi, A. A., & Alrawashdeh, N. (2025). The role and implications of finance revaluation: A comprehensive literature review. *Al-Zaytoonah Journal of Business, 1*(1), 1-12. Retrieved from https://journals.zuj.edu.jo/zjjb/Published-Papers/2025.1.2.pdf
12. Bader, A., Qtaish, A., Odeh, K., & Sa'd, H. (2025). Artificial intelligence and big data in accounting: The case of commercial banks in Jordan. *Al-Zaytoonah Journal of Business, 1*(3), 1-18. Retrieved from https://journals.zuj.edu.jo/zjjb/Published-Papers/2025.3.1.pdf
13. Ben Abdallah, M., & Bahloul, S. (2025). The influence of environmental performance, social responsibility and governance on the bank performance in MENASA countries. *Competitiveness Review: An International Business Journal.* https://doi.org/10.1108/CR-01-2025-0001
14. Berman, A., de Fine Licht, K., & Carlsson, V. (2024). Trustworthy AI in the public sector: An empirical analysis of a Swedish labor market decision-support system. *Technology in Society, 76,* 102471. https://doi.org/10.1016/j.techsoc.2024.102471
15. Brożek, B., Furman, M., Jakubiec, M., & Kucharzyk, B. (2023). The black box problem revisited: Real and imaginary challenges for automated legal decision making. *Artificial Intelligence and Law, 32,* 427-440. https://doi.org/10.1007/s10506-023-09356-9
16. Burr, C., & Leslie, D. (2023). Ethical assurance: A practical ap-

proach to the responsible design, development, and deployment of data-driven technologies. *AI and Ethics, 3*(1), 73-98. https://doi.org/10.1007/s43681-022-00178-0

17. Conway, J., & Rasool, M. (2025). *Fraud detection and financial security in the digital age: Leveraging AI-powered AML and FinTech innovation to protect financial institutions.* https://doi.org/10.13140/RG.2.2.16691.13603

18. Denwood, M. J., Kaplan, R. M., McKendrick, I. J., Thamsborg, S. M., Nielsen, M. K., & Levecke, B. (2023). A statistical framework for calculating prospective sample sizes and classifying efficacy results for faecal egg count reduction tests. *Veterinary Parasitology, 314,* 109867. https://doi.org/10.1016/j.vetpar.2022.109867

19. Díaz-Rodríguez, N., Del Ser, J., Coeckelbergh, M., de Prado, M. L., Herrera-Viedma, E., & Herrera, F. (2023). Connecting the dots in trustworthy artificial intelligence. *Information Fusion, 99,* 101896. https://doi.org/10.1016/j.inffus.2023.101896

20. Director, S. (2025). Does black box AI in medicine compromise informed consent? *Philosophy & Technology, 38*(2), 62. https://doi.org/10.1007/s13347-025-00860-1

21. Elahi, M., Afolaranmi, S. O., Martinez Lastra, J. L., & Perez Garcia, J. A. (2023). A comprehensive literature review of AI applications through the lifecycle of industrial equipment. *Discover Artificial Intelligence, 3*(1), 43. https://doi.org/10.1007/s44163-023-00089-x

22. Gofman, M., & Jin, Z. (2024). Artificial intelligence, education, and entrepreneurship. *The Journal of Finance, 79*(1), 631-667. https://doi.org/10.1111/jofi.13302

23. Guo, J., Jia, F., Yan, F., & Chen, L. (2023). E-commerce supply chain finance for SMEs: The role of green innovation. *International Journal of Logistics Research and Applications, 27*(9), 1596-1615. https://doi.org/10.1080/13675567.2023.2167959

24. Hasan, M. M., & Lu, Z. (2023). Nexus among financial inclusion and sustainability in Asia: Role of banking sector. *Environmental Science and Pollution Research, 30*(22), 62481-62493. https://doi.org/10.1007/s11356-023-26028-y

25. Hassija, V., Chamola, V., Mahapatra, A., Singal, A., Goel, D., Huang, K., Scardapane, S., Spinelli, I., Mahmud, M., & Hussain, A. (2024). Interpreting black-box models: A review on explainable artificial intelligence. *Cognitive Computation, 16*(1), 45-74. https://doi.org/10.1007/s12559-023-10179-8

26. Horobets, N., Reznik, O., Maliyk, V., Vyhivskyi, I., & Bobrishova, L. (2025). Artificial intelligence technologies in banking: Challenges and opportunities for anti-money laundering. *Journal of Money Laundering Control, 28*(4-5), 593-608. https://doi.org/10.1108/JMLC-03-2025-0041

27. Kasem, M. S., Hamada, M., & Taj-Eddin, I. (2024). Customer profiling, segmentation, and sales prediction using AI in direct marketing. *Neural Computing and Applications, 36*(9), 4995-5005. https://doi.org/10.1007/s00521-023-09339-6

28. Khattak, B. H. A., Shafi, I., Khan, A. S., Flores, E. S., Lara, R. G., Samad, M. A., & Ashraf, I. (2023). A systematic survey of AI models in financial market forecasting. *IEEE Access, 11,* 125359-125380. https://doi.org/10.1109/ACCESS.2023.3330156

29. Kocaoglu, B., & Kirmizi, M. (2025). Prescriptive digital transformation maturity model: A development and validation study. *Kybernetes, 54*(5), 2662-2705. https://doi.org/10.1108/K-02-2023-0243

30. Koskelainen, T., Kalmi, P., Scornavacca, E., & Vartiainen, T. (2023). Financial literacy in the digital age: A research agenda. *Journal of Consumer Affairs, 57*(1), 507-528. https://doi.org/10.1111/joca.12510

31. Kumar, H., Tuli, N., Singh, R. K., Arya, V., & Srivastava, R. (2024). Exploring the role of augmented reality as a new brand advocate. *Journal of Consumer Behaviour, 23*(2), 620-638. https://doi.org/10.1002/cb.2227

32. Kurum, E. (2023). RegTech solutions and AML compliance: What future for financial crime? *Journal of Financial Crime, 30*(3), 776-794. https://doi.org/10.1108/JFC-04-2020-0051

33. Mamakou, X. J., Zaharias, P., & Milesi, M. (2024). Measuring customer satisfaction in electronic commerce: The impact of e-service quality and user experience. *International Journal of Quality & Reliability Management, 41*(3), 915-943. https://doi.org/10.1108/IJQRM-07-2021-0215

34. Marti, C. L., Liu, H., Kour, G., Bilgihan, A., & Xu, Y. (2024). Leveraging artificial intelligence in firm-generated online customer communities. *Journal of Service Management, 35*(3), 438-458. https://doi.org/10.1108/JOSM-10-2023-0443

35. Mennella, C., Maniscalco, U., De Pietro, G., & Esposito, M. (2024). Ethical and regulatory challenges of AI technologies in healthcare: A narrative review. *Heliyon, 10*(4), e26297. https://doi.org/10.1016/j.heliyon.2024.e26297

36. Mogaji, E., & Nguyen, N. P. (2022). Managers' understanding of AI in marketing financial services. *International Journal of Bank Marketing, 40*(6), 1272-1298. https://doi.org/10.1108/IJBM-09-2021-0440

37. Moro-Visconti, R., Cruz Rambaud, S., & López Pascual, J. (2023). Artificial intelligence-driven scalability and sustainability of traditional firms. *Humanities and Social Sciences Communications, 10*(1), 1-14. https://doi.org/10.1057/s41599-023-02214-8

38. Morshed, A. (2024a). Assessing the economic impact of IFRS adoption on financial transparency and growth in the Arab Gulf countries. *Economies, 12*(8), 209. https://doi.org/10.3390/economies12080209

39. Morshed, A. (2024b). Evaluating the effects of IFRS 9 on Jordanian banks' credit and financial metrics. *Banks and Bank Systems, 19*(4), 70-83. https://doi.org/10.21511/bbs.19(4).2024.06

40. Morshed, A. (2024c). Mathematical Analysis of Working Capital

http://dx.doi.org/10.21511/bbs.21(1).2026.03

Management in MENA SMEs: Panel Data Insights. *Applied Mathematics & Information Sciences, 18*(1), 111-124. Retrieved from https://digitalcommons.aaru.edu.jo/amis/vol18/iss1/11/

41. Morshed, A. (2025a). Ethical challenges in designing sustainable business models for responsible consumption and production. *Management & Sustainability: An Arab Review, 5*(1), 86-108. https://doi.org/10.1108/MSAR-09-2024-0131

42. Morshed, A. (2025b). Navigating tradition and modernity: Digital accounting and financial integration in family-owned enterprises in the Arab Gulf. *Sustainable Futures, 9,* 100680. https://doi.org/10.1016/j.sftr.2025.100680

43. Morshed, A., & Khrais, L. T. (2025). Cybersecurity in digital accounting systems: Challenges and solutions in the Arab Gulf region. *Journal of Risk and Financial Management, 18*(1), 41. https://doi.org/10.3390/jrfm18010041

44. Morshed, A., Ramadan, A., Maali, B., Khrais, L. T., & Baker, A. A. R. (2024). Transforming accounting practices: The impact and challenges of business intelligence integration in invoice processing. *Journal of Infrastructure, Policy and Development, 8*(6), 4241. Retrieved from https://systems.enpress-publisher.com/index.php/jipd/article/view/4241

45. Mühlhoff, R. (2023). Predictive privacy: Collective data protection in AI and big data. *Big Data & Society, 10*(1). https://doi.org/10.1177/20539517231166886

46. Nair, A. J., Manohar, S., Mittal, A., & Chaudhry, R. (2024). Unleashing digital frontiers: Bridging realities of AR, VR, and the metaverse. In *The Metaverse Dilemma* (pp. 85-112). Emerald Publishing. https://doi.org/10.1108/978-1-83797-524-220241006

47. Nastoska, A., Jancheska, B., Rizinski, M., & Trajanov, D. (2025). Evaluating trustworthiness in AI: Risks, metrics, and applications across industries. *Electronics, 14*(13), 2717. https://doi.org/10.3390/electronics14132717

48. Ooi, K.-B., Tan, G. W.-H., Al-Emran, M., Al-Sharafi, M. A., Capatina, A., Chakraborty, A., Dwivedi, Y. K., Huang, T.-L., Kar, A. K., & Lee, V.-H. (2025). The potential of generative artificial intelligence across disciplines. *Journal of Computer Information Systems, 65*(1), 76-107. https://doi.org/10.1080/08874417.2023.2261010

49. Oreqat, A. (2021). The degree of satisfaction of Facebook users about its features, usage motives and achieved gratifications: "An applied study on students of the Faculty of Mass Communication at the Middle East University" to attract attention. *Middle East Journal of Communication Studies, 1*(1), Article 1. (In Arabic). https://doi.org/10.71220/2585-001-001-001

50. Patrício, L., Varela, L., & Silveira, Z. (2025). Implementation of a sustainable framework through robotic process automation and big data. *Processes, 13*(2), 536. https://doi.org/10.3390/pr13020536

51. Ramzani, S. R., Konhaeusner, P., Olaniregun, O. A., Abu-Alkheil, A., & Alsharari, N. (2024). Integrating AI-driven green finance strategies for sustainable development. *European Journal of Business and Management Research, 9*(2), 43-55. https://doi.org/10.24018/ejbmr.2024.9.2.2277

52. Roshanaei, M. (2024). Towards best practices for mitigating AI implicit bias in higher education. *Education and Information Technologies, 29,* 18959-18984. https://doi.org/10.1007/s10639-024-12605-2

53. Şahin, E., Arslan, N. N., & Özdemir, D. (2025). Unlocking the black box: Interpretability and reliability in deep learning. *Neural Computing and Applications, 37*(2), 859-965. https://doi.org/10.1007/s00521-024-10437-2

54. Salhab, H., Zoubi, M., Khrais, L. T., Estaitia, H., Harb, L., Al Huniti, A., & Morshed, A. (2025). AI-driven sustainable marketing in Gulf Cooperation Council retail. *Administrative Sciences, 15*(1), 20. https://doi.org/10.3390/admsci15010020

55. Sampat, B., Mogaji, E., & Nguyen, N. P. (2024). The dark side of FinTech in financial services. *International Journal of Bank Marketing, 42*(1), 38-65. https://doi.org/10.1108/IJBM-07-2022-0328

56. Sathupadi, K., Achar, S., Bhaskaran, S. V., Faruqui, N., & Uddin, J. (2025). BankNet: Real-time big data analytics for secure internet banking. *Big Data and Cognitive Computing, 9*(2), 24. https://doi.org/10.3390/bdcc9020024

57. Schmitt, M. (2023). Automated machine learning: AI-driven decision making in business analytics. *Intelligent Systems with Applications, 18,* 200188. https://doi.org/10.1016/j.iswa.2023.200188

58. Shaban, O. S., & Omoush, A. (2025). AI-driven financial transparency and corporate governance: Evidence from Jordan. *Sustainability, 17*(9), 3818. https://doi.org/10.3390/su17093818

59. Shakir, M. A., Appana, A. R., Khalid, W., Rajamanickam, P. J. K. S., & Ahmad, M. I. (2025). Advancing insights into building electrical energy consumption: A comprehensive review of conventional and artificial intelligence methods. *Advances in Building Energy Research, 19*(5), 533-576. https://doi.org/10.1080/17512549.2025.2513282

60. Smith, L., & Lamprecht, C. (2024). Identifying the limitations associated with machine learning techniques in accounting tasks. *Journal of Financial Reporting and Accounting, 23*(6). https://doi.org/10.1108/JFRA-05-2023-0280

61. Taqa, S. B. A. (2025). The mediating role of remote communication on the relationship between electronic human resource management practices and organizational performance in Iraqi commercial banks. *Middle East Journal of Communication Studies, 5*(1), Article 2. (In Arabic). https://doi.org/10.71220/2585-005-001-001

62. Vancsura, L., Tatay, T., & Bareith, T. (2025). Navigating AI-driven financial forecasting: A systematic review of current status and critical research gaps. *Forecasting, 7*(3), 36. https://doi.org/10.3390/forecast7030036

APPENDIX A

Table A1. Distribution of sampled institutions by country and sector

Country	Banks	Insurance	Fintech	Investment	Total
United Arab Emirates	3	1	1	–	5
Saudi Arabia	2	1	1	–	4
Bahrain	1	1	1	–	3
Kuwait	1	1	1	–	3
Qatar	2	1	–	–	3
Oman	1	–	1	–	2
Total	10	5	5	–	20

APPENDIX B. QUESTIONNAIRE ITEMS AND CONSTRUCT MAPPING

Survey Title: *AI-Driven and Traditional Predictive Models Performance Survey*
Target Respondents: Managers, analysts, risk officers, data/IT specialists in GCC financial institutions
Estimated Time: 7-10 minutes

Section 1: Participant information

Instructions:

This survey examines your institution's use of predictive models (AI-driven or traditional). Your responses are anonymous and confidential.

Q1. Country of your institution

☐ United Arab Emirates
☐ Saudi Arabia
☐ Bahrain
☐ Kuwait
☐ Qatar
☐ Oman

Q2. Type of institution

☐ Bank
☐ Insurance company
☐ FinTech firm
☐ Investment/Asset management
☐ Other (please specify): _____

Q3. Your department

☐ Risk management
☐ Credit/Loans
☐ IT/Data analytics
☐ Customer services
☐ Operations
☐ Other: _____

http://dx.doi.org/10.21511/bbs.21(1).2026.03

Q4. Years of experience

☐ Less than 2 years
☐ 2–5 years
☐ 6–10 years
☐ More than 10 years

Q5. What type of predictive model does your institution primarily use?

☐ AI-driven predictive model (machine learning / deep learning)
☐ Traditional statistical model (regression, time-series, scoring models)
☐ Both in combination
☐ Not sure

Section 2: Predictive model performance

Instructions:

Please indicate the extent to which you agree with each statement.
1 = Strongly Disagree 5 = Strongly Agree

All items are presented in a **real questionnaire grid** exactly as used in institutional surveys.

Table B1. Predictive accuracy (How accurate and reliable is your predictive model?)

Item Code	Statement	1	2	3	4	5
PA1	The model generates forecasts with high accuracy					
PA2	The model reduces forecasting errors compared to past tools					
PA3	The model captures important market and financial trends					
PA4	The model enhances the reliability of financial decisions					
PA5	Forecasts from this model closely match real outcomes					
PA6	The model handles complex and high-volume datasets					
PA7	The model enhances risk and performance prediction quality					
PA8	Overall, this model improves prediction accuracy					

Table B2. Operational efficiency (How well does the model improve internal operations?)

Item Code	Statement	1	2	3	4	5
OE1	The model reduces the time required for analytical tasks					
OE2	The model automates repetitive processes effectively					
OE3	The model reduces reliance on manual data work					
OE4	The model improves workflow efficiency					
OE5	The model helps decrease operational costs					
OE6	The model speeds up reporting and decision processes					
OE7	The model increases overall staff productivity					

Table B3. Risk-management effectiveness (How well does the model support risk identification and mitigation?)

Item Code	Statement	1	2	3	4	5
RM1	The model improves early detection of financial risks					
RM2	The model identifies anomalies more accurately					
RM3	The model helps anticipate emerging threats					
RM4	The model offers clear insights into risk exposures					
RM5	The model supports timely and effective mitigation actions					
RM6	The model strengthens compliance with regulatory requirements					
RM7	Overall, the model improves risk-management performance					

Table B4. Customer satisfaction (How does the model influence customer experience?)

Item Code	Statement	1	2	3	4	5
CS1	The model enhances service personalization					
CS2	The model anticipates customer needs more accurately					
CS3	The model improves the relevance of the services offered					
CS4	The model improves responsiveness to customer inquiries					
CS5	The model increases customer trust in digital services					
CS6	The model provides better targeting of financial products					
CS7	Customers report higher satisfaction with model-supported services					
CS8	Overall, the model improves customer experience					

Section 3: General assessment

Q6. Overall, how satisfied are you with your institution's current predictive model?

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

Q7. In your opinion, does AI adoption improve institutional performance?

☐ Yes
☐ No
☐ Partially
☐ Not sure

Q8. Would you recommend expanding AI use in your institution?

☐ Yes
☐ No
☐ Maybe

http://dx.doi.org/10.21511/bbs.21(1).2026.03