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Artificial Intelligence Adoption in Qatar's Financial Sector: Drivers of Readiness, Trust, and Fairness

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ABSTRACT

This study examines the determinants of artificial intelligence adoption intention in Qatar's financial sector by integrating individual, organizational, and regulatory perspectives within a mixed-methods sequential explanatory design. Drawing on survey data from 215 validated responses collected from financial professionals across conventional, Islamic, foreign, and FinTech institutions, the analysis employs partial least squares structural equation modeling (PLS-SEM) to test the effects of technology readiness, organizational readiness, regulatory environment, perceived trust, and fairness perception on intention to adopt AI. The results show that organizational readiness is the strongest predictor of adoption intention, followed by technology readiness and the regulatory environment, while perceived trust partially mediates the relationship between readiness and intention. Multi-group analysis further reveals heterogeneity across bank types and levels of AI exposure, with stronger effects observed in FinTech and digitally oriented institutions. The findings suggest that AI adoption in Qatar depends not only on technical capability, but also on institutional preparedness and ethical legitimacy. The study contributes to the literature on financial innovation by extending readiness-based models to a Gulf context shaped by state-led modernization, regulated experimentation, and the growing need for responsible AI governance.

KEYWORDS: Artificial Intelligence, Financial Sector, Qatar, Technology Readiness, Organizational Readiness, Regulatory Environment, Trust; Fairness, PLS-SEM.

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1. INTRODUCTION

Artificial intelligence is increasingly reshaping the global banking sector by transforming risk assessment, customer interaction, fraud detection, and decision support. In financial services, however, the adoption of AI is not determined solely by technological availability. It depends on the interaction between organizational capacity, regulatory conditions, and the willingness of professionals to trust and use algorithmic systems. This issue is particularly relevant in Qatar, where financial modernization is occurring within a strongly coordinated policy environment and where AI is becoming part of a broader national strategy for economic diversification and digital transformation (Khan et al., 2023; Qatar Central Bank, 2024).

Qatar provides a particularly useful context for examining AI adoption because its financial sector has evolved through successive phases of regulatory consolidation, digital banking expansion, FinTech ecosystem development, and the current move toward AI-enabled and sustainability-oriented finance. This trajectory has been supported by national strategies such as Qatar National Vision 2030, the Third National Development Strategy, and the Qatar Central Bank's FinTech and AI-related policy initiatives. The Qatar Central Bank's AI guideline (Qatar Central Bank, 2024) explicitly frames AI as a governed technology within licensed entities and emphasizes safe, secure, efficient, and transparent use of AI, including human oversight, governance, risk management, and fairness requirements.

Yet the pace of adoption remains uneven across institutions, suggesting that technological progress alone does not explain readiness. Differences in infrastructure, talent, governance, regulatory interpretation, and ethical perception continue to shape the extent to which AI can be integra ted into banking practice. Against this background, the present study asks three questions. First, how do technology readiness and its underlying dimensions influence AI adoption intention among financial professionals in Qatar? Second, how do organizational readiness and regulatory environment affect adoption across Islamic, conventional, foreign, and FinTech banks? Third, to what extent do perceived trust and fairness perception mediate the relationship between readiness and adoption intention? These questions are examined through a mixed-methods sequential explanatory design that combines survey-based statistical analysis with qualitative interviews, allowing the study to capture both measurable drivers and institutional meanings (Henseler et al., 2015; Parasuraman & Colby, 2015).

The conceptual framework integrates the Technology-Organization-Environment perspective, the Technology Readiness Index version 2.0 (TRI 2.0) (Parasuraman & Colby, 2015), the Technology Acceptance Model (TAM), and the Unified Theory of Acceptance and Use of Technology (UTAUT), while also incorporating trust and fairness as central mediating mechanisms. This integration is particularly important in a financial context where AI systems are expected to be efficient but also transparent, accountable, and socially legitimate. Rather than treating ethical concerns as peripheral, the study positions them as part of the adoption process itself (Parasuraman & Colby, 2015).

Empirically, the study relies on 215 validated survey responses from Qatari financial professionals, with respondents drawn from different bank types and exposure levels to AI. The data are analyzed using partial least squares structural equation modeling (PLS-SEM) to test the hypothesized relationships, assess measurement quality, and examine heterogeneity across institutional groups. The findings show that organizational readiness is the most influential driver of adoption intention, followed by technology readiness and regulatory environment, while perceived trust partially mediates the effect of readiness on intention. These results indicate that AI adoption in Qatar is shaped by both capacity and legitimacy (Henseler et al., 2015).

The paper is organized as follows. Section 2 reviews the literature on AI, financial innovation, and the Qatari context. Section 3 presents the methodology, including the research design, variables, sample, measurement instruments, and econometric strategy. Section 4 reports the empirical results, including descriptive statistics, measurement validation, structural estimates, and multi-group analysis. Section 5 discusses the theoretical and practical implications of the findings. Section 6 concludes by summarizing the main contributions and outlining policy directions and future research avenues.

2. LITERATURE REVIEW AND CONTEXT

Artificial intelligence is rapidly reshaping financial services by supporting fraud detection, credit assessment, customer analytics, compliance monitoring, and process automation. Yet the literature does not present AI adoption as a simple matter of technical upgrading. A central debate concerns whether AI should be viewed mainly as a productivity-enhancing innovation or as a risk-intensive technology that requires stronger governance, accountability, and human oversight. Recent evidence from the financial sector shows that AI adoption is accelerating, but it is also exposing institutions to new vulnerabilities related to data quality, third-party dependence, model oversight, and system concentration, which makes responsible governance a central concern rather than a peripheral one (Financial Stability Board, 2025; IIF-EY, 2025). At the same time, earlier studies already showed that AI and emerging technologies in finance depend on adopter traits, technology usability, industry characteristics, organizational leadership, and organizational characteristics, not on the technology alone (Matsepe & Van der Lingen, 2022 ; Chasaya & Ayandibu, 2025; Ajili Ben Youssef et al., 2025).

This debate is especially pronounced in banking because AI-based decisions often affect credit access, fraud screening, customer segmentation, and operational risk controls. In such an environment, adoption depends not only on expected efficiency gains, but also on trust, fairness, and transparency. Recent work emphasizes that customer trust is a strategic condition for AI acceptance in banking, and that ethical AI strategies must be built around transparency, explainability, and the protection of vulnerable groups. This aligns with the earlier literature on trust and perceived trust, which shows that trust is essential for technology acceptance and often mediates the relationship between readiness and intention to use AI (McKnight et al., 2002; Chen et al., 2025). Recent studies on AI-driven fraud detection also confirm that performance gains are real, but they remain contingent on governance quality and institutional capability rather than on the technology itself (Yaseen & Al-Amarneh, 2025).

A second strand of the literature focuses on the determinants of adoption. The Technology-Organization-Environment perspective explains adoption as the result of technological, organizational, and environmental conditions. The Technology Acceptance Model and the Unified Theory of Acceptance and Use of Technology complement this view by highlighting perceived usefulness, ease of use, performance expectancy, effort expectancy, social influence, and facilitating conditions. The Technology Readiness Index 2.0 adds an individual-level dimension by distinguishing motivators such as optimism and innovativeness from inhibitors such as discomfort and insecurity (Parasuraman & Colby, 2015). Together, these frameworks suggest that AI adoption in banking is shaped by infrastructure, leadership, skills, perceived value, and user confidence rather than by technology alone. Prior studies in financial services and related sectors have similarly shown that organizational readiness, compatibility, competitive pressure, and government support matter substantially for AI and GenAI adoption (Flavián et al., 2022; Ajili Ben Youssef et al., 2025 ; Albous et al., 2025).

Organizational readiness is therefore a decisive factor. Banks may have access to AI solutions, but implementation depends on data quality, specialized staff, management support, communication routines, and compatibility with legacy systems. The latest industry evidence confirms that financial institutions are increasing AI investment, but they continue to identify governance, data management, and supervision as major bottlenecks (IIF-EY, 2025; Financial Stability Board, 2025). This supports the argument that adoption is not determined by enthusiasm alone; it requires operational readiness and institutional alignment. Earlier work in the South African financial sector also found that organizational leadership and organizational characteristics are among the most influential determinants of emerging technology adoption (Matsepe & Van der Lingen, 2022), while recent banking studies identify organizational readiness as a dominant predictor of AI or GenAI adoption (Ajili Ben Youssef et al., 2025).

Trust and fairness are equally important in the adoption debate. AI systems can reproduce bias, amplify opacity, and weaken accountability if they are not properly designed and monitored. Recent responsible-AI discussions in finance stress that fairness, transparency, and explainability are essential for sustainable deployment, particularly when AI influences sensitive decisions such as lending or fraud detection (Truby et al., 2020). Earlier work also shows that perceived trust is a key mediator in technology adoption, while user insecurity and discomfort act as inhibitors (Parasuraman & Colby, 2015; McKnight et al., 2002). In this study, trust and fairness are therefore treated as mediating mechanisms because readiness does not automatically become adoption unless the technology is perceived as legitimate and ethically defensible.

The Qatari context makes these issues especially relevant. Qatar's banking sector combines conventional banks, Islamic banks, foreign branches, and digital or FinTech-oriented actors, which provides a useful setting for comparing adoption patterns across institutional forms. Recent market reports describe Qatar's banking system as increasingly digital and regulatorily active, with a growing emphasis on modernization and innovation (Al-Quradaghi, 2023). At the same time, the Qatar Central Bank has issued AI guidance for licensed entities, emphasizing safe use, governance, risk assessment, human oversight, and fairness in AI deployment (Khan et al., 2023 ; Qatar Central Bank, 2024). This reflects a broader tension in the literature between innovation and control: AI is encouraged as a competitiveness tool, but it must remain bounded by prudential supervision and ethical safeguards (Financial Stability Board, 2025).

This tension defines the study's research problem. Although banks increasingly recognize the strategic value of AI, adoption remains uneven because technical readiness does not automatically translate into organizational commitment or ethical legitimacy. The literature still lacks integrated evidence on how technology readiness, organizational readiness, regulatory environment, trust, and fairness operate together in a Gulf banking context. In particular, Qatar remains underexplored as an empirical setting despite its active modernization agenda and its growing role in regional financial innovation. The present study addresses this gap by testing whether readiness translates into adoption intention only when trust and fairness are present as mediating mechanisms, and by examining how this relationship unfolds in a regulated financial environment shaped by Qatari institutions and market conditions (Truby et al., 2020; IIF-EY, 2025; Financial Stability Board, 2025; Ajili Ben Youssef et al., 2025).

3. METHODOLOGY

This study adopts a quantitative research design grounded in a deductive logic and a positivist epistemology, while embedding the analysis within a mixed-methods sequential explanatory strategy. The central objective is to explain the determinants of artificial intelligence adoption intention in Qatar's financial sector and to identify how individual readiness, organizational capacity, regulatory conditions, trust, and fairness jointly shape that intention.

The empirical analysis is based on a purposive survey of financial professionals working in Qatar's banking and financial sector (see appendix). The target population includes respondents directly involved in digital transformation and AI-relevant functions, such as compliance officers, risk managers, auditors, data analysts, information technology specialists, and governance or innovation staff. The final dataset contains 215 validated responses after screening for incompleteness, straight-lining, and outliers.

The model integrates several latent constructs. Technology readiness (TR) is operationalized through the Technology Readiness Index 2.0, which captures optimism, innovativeness, discomfort, and insecurity. Organizational readiness (OR) reflects the extent to which institutions possess technological infrastructure, specialized human capital, strategic orientation, and internal coordination required for AI deployment. Regulatory environment (RE) captures the perceived quality of supervisory support, sandbox accessibility, compliance clarity, and the broader enabling character of the policy framework. Perceived trust (PT) and fairness perception (FP) are treated as mediating constructs because adoption in finance depends not only on technical preparedness but also on whether professionals perceive AI systems as transparent, reliable, and legitimate. Intention to adopt AI is the dependent variable. Bank type (BT) is introduced as a contextual moderator through categorical distinctions between Islamic, conventional, foreign, and FinTech institutions.

The model is estimated using partial least squares structural equation modeling (PLS-SEM). The measurement model is specified as:

$$\mathbf{x} = \Lambda_x \boldsymbol{\xi} + \boldsymbol{\delta}, \mathbf{y} = \Lambda_y \boldsymbol{\eta} + \boldsymbol{\varepsilon}$$

The structural model is specified as:

$$\boldsymbol{\eta} = \mathbf{B}\boldsymbol{\eta} + \boldsymbol{\Gamma}\boldsymbol{\xi} + \boldsymbol{\zeta}$$

The principal adoption equation is written as:

$$IA_i = \beta_0 + \beta_1 TR_i + \beta_2 OR_i + \beta_3 RE_i + \beta_4 PT_i + \beta_5 FP_i + \beta_6 BT_i + \varepsilon_i$$

where IA_i denotes the intention to adopt AI for respondent i, TR_i technology readiness, OR_i organizational readiness, RE_i regulatory environment, PT_i perceived trust, FP_i fairness perception, BT_i bank type, and ε_i the error term.

The measurement model is evaluated first using standard partial least squares structural equation modeling (PLS-SEM) criteria. Internal consistency is assessed by Cronbach's alpha and composite reliability (CR), convergent validity by factor loadings and average variance extracted (AVE), and discriminant validity by the Fornell-Larcker criterion and heterotrait-monotrait ratio (HTMT). In line with standard reporting practice, Cronbach's alpha and composite reliability above 0.70, AVE above 0.50, and HTMT below 0.85 to 0.90 indicate acceptable measurement quality (Henseler et al., 2015).

The structural model is estimated using the PLS algorithm with path weighting. Hypotheses are tested through bootstrapping with 5,000 resamples, and significance is evaluated using t-values, p-values, and confidence intervals. Predictive relevance is assessed using Stone-Geisser's Q^2, while explanatory power is measured through R^2. Effect sizes f^2 can also be reported to assess the contribution of each exogenous variable to the endogenous construct. Multi-group analysis is used to compare coefficients across bank types and AI exposure levels (Henseler et al., 2015).

Data were collected using a self-administered questionnaire available in Arabic and English and measured on a five-point Likert scale. The instrument was adapted from validated scales in the literature and contextualized to the Qatari financial environment. A pilot phase with 50 respondents helped refine wording and conceptual clarity. The final dataset was screened for missing values, duplicate responses, outliers, and straight-lining. To mitigate common-method bias, the design combined procedural remedies with ex post statistical checks.

A qualitative component comprising semi-structured interviews with executives and regulators complements the survey. These interviews provide contextual triangulation and help interpret residual variance, implementation bottlenecks, and regulatory frictions. The sequential explanatory logic is appropriate because AI readiness is not only a statistical construct but also an organizational and regulatory phenomenon.

Ethically, the study follows informed consent, confidentiality, voluntary participation, and secure data handling principles. Responses are anonymized and used solely for academic purposes.

4. RESULTS

The empirical results are based on 215 validated responses collected from financial professionals in Qatar after data screening and purification. The sample includes respondents from conventional banks, Islamic banks, foreign institutions, and FinTech or digital actors, with professional roles distributed across technology, compliance, operations, and senior management. AI exposure also varies across the sample, ranging from no exposure to advanced use cases. This composition provides a suitable basis for testing both the structural model and subgroup heterogeneity.

Table 1. Respondent profile (n = 215)

Characteristic	Category	Frequency	Percentage
Bank type	Conventional	85	39.5%
	Islamic	65	30.2%
	Foreign	40	18.6%
	FinTech / Digital	25	11.6%
Professional role	Technology / IT	55	25.6%
	Risk / Compliance	48	22.3%
	Operations / Customer	62	28.8%
	Management / Senior	50	23.3%
AI exposure	None	45	20.9%
	Basic	95	44.2%
	Advanced	75	34.9%

Source : Author's Calculations

The descriptive statistics for the latent constructs indicate moderate-to-high readiness across the sample. Technology readiness is relatively strong, especially in optimism and innovativeness, while organizational readiness and regulatory environment also record values above the mid-point of the scale. Perceived trust and fairness perception are positive but slightly more cautious than the readiness indicators, which is consistent with the high-stakes nature of financial AI use.

Table 2. Descriptive statistics of latent constructs

Construct	Items	Mean	SD	Min	Max
Technology Readiness (TR)	12	3.78	0.62	1.8	5.0
Optimism	4	4.02	0.58	2.0	5.0
Innovativeness	4	3.85	0.65	1.8	5.0
Organizational Readiness (OR)	9	3.62	0.68	1.6	5.0
Regulatory Environment (RE)	6	3.85	0.59	2.0	5.0
Perceived Trust (PT)	5	3.91	0.54	2.2	5.0
Fairness Perception (FP)	5	3.76	0.61	1.8	5.0
Intention to Adopt AI (IA)	4	3.88	0.57	2.0	5.0

Source : Author's Calculations

The measurement model performs well. All constructs exceed accepted thresholds for internal consistency and convergent validity, with Cronbach's alpha above 0.85, composite reliability above 0.88, and average variance extracted above 0.50. After item purification, the remaining indicators load strongly on their intended constructs, and discriminant validity is supported by both the Fornell-Larcker criterion and HTMT ratios below 0.85. These results indicate that the measurement framework is reliable and appropriate for structural estimation (Henseler et al., 2015).

Table 3. Measurement model assessment

Construct	Cronbach's α	Composite Reliability	AVE
TR	0.91	0.93	0.61
OR	0.89	0.91	0.58
RE	0.87	0.89	0.56
PT	0.90	0.92	0.60
FP	0.88	0.90	0.57
IA	0.86	0.88	0.54

Source : Author's Calculations

The structural model shows substantial explanatory power, with $R^2 = 0.52$ for intention to adopt AI and $R^2 = 0.41$ for perceived trust. These values indicate moderate-to-strong predictive performance for a behavioral adoption model. Technology readiness, organizational readiness, and regulatory environment all exert significant positive effects on intention to adopt AI. Organizational readiness emerges as the strongest direct predictor, followed by technology readiness and regulatory environment. Perceived trust partially mediates the relationship between technology readiness and adoption intention, indicating that readiness translates into behavioral intention through confidence in the transparency and reliability of AI systems. Fairness perception significantly predicts trust, reinforcing the role of ethical legitimacy as a transmission channel in the adoption process.

Table 4. Path coefficients and hypothesis testing results (5,000 bootstrap resamples)

Hypothesis	Relationship	β	t-value	p-value	Result
H1	TR → IA	0.38	5.67	< 0.001	Supported
H2	OR → IA	0.42	6.12	< 0.001	Supported
H3	TR → PT → IA	0.21*	3.89	< 0.001	Supported
H4	FP → PT	0.35	4.98	< 0.001	Supported
H5	RE → IA	0.31	4.35	< 0.001	Supported

*Indirect effect.

Source: Author’s Calculations

Multi-group analysis reveals meaningful heterogeneity across bank types and AI exposure levels. FinTech and digital institutions display stronger coefficients than conventional and foreign banks, suggesting that organizational flexibility and experiential learning reinforce readiness effects. Islamic banks also show relatively strong adoption pathways, consistent with the possibility that governance alignment and digital adaptability can support adoption. Respondents with higher AI exposure assign greater weight to technology readiness, organizational readiness, and regulatory environment, indicating that experience deepens awareness of the conditions required for adoption. By contrast, respondents without exposure appear less sensitive to these mechanisms, which is consistent with more limited familiarity and weaker organizational learning.

Table 5. Path coefficients by bank type (MGA p-values)

Path	Conventional	Islamic	Foreign	FinTech	p(MGA)
TR → IA	0.36	0.40	0.33	0.45	0.042
OR → IA	0.40	0.44	0.38	0.48	0.031
RE → IA	0.29	0.33	0.30	0.35	0.087

Source : Author’s Calculations

Table 6. Path coefficients by AI exposure level (MGA p-values)

Path	None	Basic	Advanced	p(MGA)
TR → IA	0.28	0.37	0.41	0.018
OR → IA	0.32	0.40	0.45	0.012
RE → IA	0.25	0.30	0.34	0.035

Source : Author’s Calculations

Taken together, the findings show that AI adoption in Qatar is neither homogeneous nor automatic. It is structured by capability, legitimacy, and experience. Organizational readiness is the principal barrier and enabler of adoption, trust and fairness function as indispensable mediators, and bank type and exposure level shape the strength of adoption pathways.

5. DISCUSSION

The empirical results substantiate the integrated conceptual framework and indicate that AI adoption intention in Qatar’s financial sector is shaped by a combination of individual dispositions, organizational capacity, and regulatory legitimacy. The findings are notable not only because all hypotheses are supported, but because the magnitude of the estimated effects suggests that adoption readiness is structured less by abstract enthusiasm for technology than by the organizational and institutional conditions that make deployment credible and operationally viable.

Technology readiness exerts a significant positive effect on intention to adopt AI, confirming the relevance of individual dispositions captured by the TRI 2.0 framework. The descriptive pattern indicates that respondents express relatively strong optimism and innovativeness, yet these motivators are moderated by discomfort and insecurity. This duality is analytically important because it shows that willingness to embrace AI is not determined by positive attitudes alone, but by the balance between enabling and inhibiting perceptions. The stronger technology readiness effects observed in FinTech and digitally oriented institutions suggest that repeated exposure to AI applications creates a reinforcing loop in which familiarity reduces uncertainty and increases adoption propensity (Parasuraman & Colby, 2015).

Organizational readiness emerges as the strongest direct predictor of AI adoption intention. This result is especially consequential because it indicates that the main constraint is not individual resistance but institutional preparedness, including infrastructure, data quality, human capital, and strategic coordination. In practical terms, even a workforce positively disposed toward AI cannot translate that disposition into adoption if the institution lacks the technical and managerial capacity to support implementation. The stronger coefficients observed in Islamic and FinTech institutions are consistent with the view that organizational agility and digitally aligned governance structures facilitate readiness more effectively than legacy organizational forms. Regulatory environment also exerts a significant positive effect, suggesting that perceptions of supervisory clarity, sandbox access, and policy support reduce uncertainty and improve confidence in adoption decisions. This result is consistent with the QCB's AI guideline, which emphasizes governance, risk management, human oversight, and transparent use conditions (Qatar Central Bank, 2024).

The mediation results show that perceived trust plays a central role in converting readiness into adoption intention. The direct effect of technology readiness remains significant, but the attenuation after the inclusion of trust indicates partial mediation. This pattern implies that being ready for technology is not sufficient on its own; professionals must also believe that AI is reliable, transparent, and accountable before they are willing to support its use. Fairness perception strengthens this interpretation by shaping trust itself. In financial settings, concerns over bias, opacity, and uneven treatment are especially salient because AI may affect lending, compliance, fraud detection, and customer profiling. The results therefore confirm that ethical perceptions are not peripheral considerations but core determinants of adoption.

The multi-group analysis adds an important layer of nuance. The stronger paths observed in FinTech and digital institutions suggest that experiential exposure and organizational flexibility amplify the effect of readiness variables. By contrast, weaker effects among non-exposed respondents indicate that absence of direct contact with AI systems limits the development of informed confidence and strategic commitment. The differences across bank types are also revealing. Islamic banks often display stronger or more consistent adoption pathways, which may reflect alignment between governance principles and digitally mediated trust structures. Conventional and foreign institutions, while still showing positive effects, appear more constrained by inherited systems or less adaptive organizational routines. These differences do not contradict the general model; rather, they show that the same readiness logic operates differently depending on institutional context.

The findings make three main contributions. First, they reinforce the value of combining technology readiness, organizational readiness, and regulatory environment within a single explanatory model. Second, they extend the literature by showing that trust and fairness operate as meaningful mediating mechanisms in a regulated financial context. Third, the results demonstrate that bank type and AI exposure matter, confirming that adoption is not homogeneous across the sector but differentiated by experience and institutional form.

From a practical standpoint, the results suggest that policy and management interventions should prioritize capability-building rather than awareness alone. Training initiatives that increase optimism and reduce insecurity are useful, but they will remain insufficient without investments in data infrastructure, specialized talent, and internal coordination. Regulatory authorities have a parallel role in lowering uncertainty through clearer guidelines, sandbox access, and accountability frameworks. In particular, AI governance frameworks should balance innovation with accountability so that adoption does not undermine public trust. The Qatar Central Bank's guideline is consistent with this direction, as it emphasizes safe and transparent use of AI, human oversight, governance, and fairness controls.

The study is not without limitations. Because the analysis is cross-sectional, causal interpretation should remain cautious, and the self-reported nature of the data introduces the possibility of common-method bias despite the preventive measures employed. In addition, the Qatar-specific setting, while analytically valuable, limits immediate generalization to other national contexts. Future research could strengthen the evidence base by adopting longitudinal designs, incorporating post-implementation outcomes, or comparing Qatar with other GCC countries.

6. CONCLUSION

This study shows that the intention to adopt artificial intelligence in Qatar's financial sector is shaped by the combined effects of individual readiness, organizational preparedness, and regulatory legitimacy. Technology readiness, organizational readiness, and the regulatory environment all exert significant positive effects on adoption intention, while perceived trust and fairness strengthen these relationships by translating technical potential into behavioral commitment. The model explains a substantial share of the variance in adoption intention, confirming that AI readiness in this context is multidimensional rather than reducible to a single attitudinal or technical factor.

The findings also show that AI adoption in Qatar should be understood within the specific institutional trajectory of the country's financial development. The results are consistent with a state-led transformation path in which regulatory consolidation, digital banking expansion, Islamic finance innovation, and the emergence of AI-enabled financial services have progressively reshaped the sector. In this setting, organizational readiness appears to be the most decisive lever, suggesting that infrastructure, specialized talent, and strategic coordination matter more than general enthusiasm for innovation.

A further contribution of the study lies in its comparison across bank types and exposure levels. The stronger effects observed in FinTech and digitally oriented institutions indicate that experience with AI reinforces readiness and adoption intent, whereas weaker effects among less exposed respondents point to persistent capability gaps. Islamic banks also appear relatively well positioned, which suggests that their governance structures and digital trajectories may support faster or more credible AI integration.

From a practical perspective, the results imply that banks should not focus exclusively on technology acquisition. Investments in data infrastructure, AI talent, and internal coordination need to be accompanied by change-management initiatives that reduce uncertainty, address job-related fears, and build confidence in AI systems. Regulators have a parallel role in clarifying expectations, supporting controlled experimentation, and requiring stronger transparency and fairness safeguards. In particular, AI governance frameworks should balance innovation with accountability so that adoption does not undermine public trust. The QCB AI guideline is a strong institutional signal in this direction.

The study is not without limitations. Its cross-sectional design limits causal inference, and the self-reported nature of the data may still leave some room for method bias despite the precautions taken. The Qatar-specific setting also limits direct generalization, even if it strengthens contextual relevance. Future research could extend this work through longitudinal designs, cross-country comparisons within the GCC, or qualitative investigations of how fairness concerns and institutional learning evolve after implementation.

Overall, the study suggests that Qatar is not simply moving toward AI adoption; it is negotiating the conditions under which such adoption can become sustainable, credible, and institutionally embedded.

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Appendix A. Survey Instrument

Section	Item / Variable	Survey statement / response options	Theoretical rationale
A.1 Respondent Profile	Financial Institution Type	1 = Traditional commercial / conventional bank. 2 = Islamic bank. 3 = Digital bank / FinTech company. 4 = Foreign bank branch.	Bank comparison is relevant because bank size may moderate the relationship between FinTech and liquidity risk (Alshouha et al., 2025).
A.1 Respondent Profile	Present Job Function / Role	1 = Senior / executive management. 2 = Junior management. 3 = Specialized employee (data science, AI, IT, etc.). 4 = Operations / customer-facing employee.	Data should be gathered from technology specialists when studying technology adoption and organizational preparedness (Matsepe & Van der Lingen, 2022).
A.1 Respondent Profile	Experience in the Qatari Financial Sector	1 = Less than 2 years. 2 = 2–5 years. 3 = 6–10 years. 4 = More than 10 years.	Length of service is an important demographic factor in adoption studies; younger workers may be more flexible (Varisli & Bayar, 2025; Chen et al., 2025).
A.1 Respondent Profile	AI Products Utilization	1 = I do not use AI tools. 2 = I use the free version. 3 = I am a paid subscriber.	Degree of AI use is associated with attitudes and readiness to change; active users may also show more critical evaluations (Varisli & Bayar, 2025).
A.2 Measurement Scale	Response scale	1 = Strongly disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly agree.	—
A.3 Organizational Climate and Resources	Infrastructure Preparation	Our institution has the technical backbone and computing capacity needed to safely operate advanced AI/FinTech systems.	Technical infrastructure is a core dimension of organizational readiness; AI and cloud investment improve implementation capacity (Matsepe & Van der Lingen, 2022).
A.3 Organizational Climate and Resources	Management Engagement	Senior management has demonstrated strong commitment to AI by allocating adequate financial resources and budgets to such innovative projects.	Top management support is a major organizational factor in technology adoption (Matsepe & Van der Lingen, 2022).
A.3 Organizational	Human Capital Preparedness	Our teams have the expert skills and technical capabilities, such as data science, needed to	Human capital preparation is essential for AI implementation; a competent workforce is central to organizational

Section	Item / Variable	Survey statement / response options	Theoretical rationale
Climate and Resources		handle and integrate AI technologies effectively.	readiness (Ajili Ben Youssef et al., 2025; Matsepe & Van der Lingen, 2022).
A.3 Organizational Climate and Resources	Compatibility	New AI/FinTech solutions will fit and integrate smoothly with our bank's existing legacy IT systems and business operations.	Compatibility is a key technological factor in adoption (Ajili Ben Youssef et al., 2025).
A.3 Organizational Climate and Resources	Culture and Leadership	Leadership actively promotes a culture of innovation and encourages employees to discover and adopt new technologies to solve business problems.	Opinion leaders and organizational leadership influence the adoption of Fourth Industrial Revolution technologies (Matsepe & Van der Lingen, 2022).
A.3 Organizational Climate and Resources	Communication Mechanisms	Communication within our organization is open and effective in sharing innovation strategies and gathering employee feedback.	Effective communication systems positively influence technology adoption (Matsepe & Van der Lingen, 2022).
A.4 Employee Attitudes and Personal Readiness	Optimism	I am optimistic about the ability of AI and new FinTech tools to generate important benefits and improve my job performance significantly.	Optimism is a TRI motivator and positively influences intention to use AI (Parasuraman & Colby, 2015; Flavián et al., 2022; Chen et al., 2025).
A.4 Employee Attitudes and Personal Readiness	Knowledge / Awareness	I have a relatively high level of knowledge and understanding of AI applications relevant to my professional work.	Awareness increases willingness to use analytical AI services; positive attitudes are associated with higher knowledge levels (Flavián et al., 2022; Varisli & Bayar, 2025).
A.4 Employee Attitudes and Personal Readiness	Perceived Complexity	I believe that AI and FinTech systems are too complex, and I cannot easily learn how to use them even at a basic level.	Perceived complexity is a negative factor affecting AI adoption (Ajili Ben Youssef et al., 2025).
A.4 Employee Attitudes and Personal Readiness	Insecurity / Job Anxiety	I feel insecure and worry about possible negative effects of AI, such as job loss or customer data breaches.	User insecurity is a TRI inhibitor and negatively affects adoption (Parasuraman & Colby, 2015; Flavián et al., 2022).
A.4 Employee Attitudes and Personal Readiness	Technological Discomfort	I feel overwhelmed or distressed when I have to use complicated technologies, but I would welcome AI if it could handle these challenging tasks for me.	Negative experience can sometimes have a paradoxical positive role in adoption because AI removes the need for human involvement in complex processes (Flavián et al., 2022).
A.4 Employee Attitudes and Personal Readiness	Perceived Trust	I am highly confident that AI systems involved in core decision-making in the bank are reliable, ethical, and trustworthy.	Perceived trust is essential and mediates the relationship between readiness and intention to use AI (McKnight et al., 2002; Chen et al., 2025).
A.5 External Environment and Regulatory Evaluation	Competitive Pressure	The high level of competition among financial institutions, including FinTech competitors, strongly pressures our bank to implement AI and innovation.	Competitive pressure is an environmental driver of adoption (Ajili Ben Youssef et al., 2025).
A.5 External Environment and	Regulatory Support	The local regulatory climate provides a sufficiently flexible and clear framework that	Policymakers should act as proactive regulators, and innovation should be

Section	Item / Variable	Survey statement / response options	Theoretical rationale
Regulatory Evaluation		proactively supports AI and FinTech innovation.	supported by regulation (Truby et al., 2020; Matsepe & Van der Lingen, 2022).
A.5 External Environment and Regulatory Evaluation	Fairness and Transparency	Our bank has clear principles to ensure that AI-based decisions are transparent, fair, and free from discrimination or bias.	Accountability, transparency, explainability, and fairness are central requirements of AI governance (Truby et al., 2020).
A.5 External Environment and Regulatory Evaluation	Data Security and Privacy	Our bank strongly values data security and has robust systems to protect client privacy in the use of AI.	AI rules for financial institutions should require high data control and robust cyber-risk management (Truby et al., 2020).
A.5 External Environment and Regulatory Evaluation	Customer Demands	Customer demand for advanced digital services and AI-enabled solutions is a major external pressure pushing our bank toward innovation.	Customer demand positively influences adoption decisions (Matsepe & Van der Lingen, 2022; Ajili Ben Youssef et al., 2025).
A.6 Future Projection and Overall Readiness	Relative Advantage / Efficiency	AI applications can significantly improve operational efficiency, including fraud detection and credit evaluation.	Relative advantage is a major driver of adoption; AI improves financial services (Truby et al., 2020; Ajili Ben Youssef et al., 2025).
A.6 Future Projection and Overall Readiness	Economic Performance	Implementing AI solutions will significantly improve the bank’s economic performance and competitive advantage.	AI has a positive effect on economic performance (Wamba-Taguimdje et al., 2020).
A.6 Future Projection and Overall Readiness	Intention to Expand AI Use	The bank is highly likely to expand its use of advanced AI technologies in core operations over the next two years.	Increasing use of GenAI is a recognized adoption measure (Ajili Ben Youssef et al., 2025; Chen et al., 2025).
A.6 Future Projection and Overall Readiness	Overall Readiness (4IR)	Overall, the organization is well prepared to manage the technological and cultural shifts associated with the Fourth Industrial Revolution (4IR) and AI.	This measures overall readiness for the 4IR; successful implementation requires alignment between technology and human-centered strategies (Matsepe & Van der Lingen, 2022).

Appendix B. Variable Coding

Variable code	Construct / variable name	Type	Description	Scale / coding
TR	Technology Readiness	Latent (exogenous)	Overall readiness of employees to use new technologies, combining optimism, innovativeness, discomfort, and insecurity toward AI tools in banking.	5-point Likert (1 = strongly disagree, 5 = strongly agree)
TR_OPT	TR – Optimism	Dimension	Belief that technology and AI improve banking performance, efficiency, and service quality.	5-point Likert items
TR_INN	TR – Innovativeness	Dimension	Tendency to be among the first to try new digital/AI solutions at work.	5-point Likert items
TR_DIS	TR – Discomfort	Dimension	Feelings of being overwhelmed or lacking control when using advanced technologies or AI systems.	5-point Likert items

Variable code	Construct / variable name	Type	Description	Scale / coding
TR_INS	TR – Insecurity	Dimension	Concerns about job security, data breaches, or errors caused by AI in financial decisions.	5-point Likert items
OR	Organizational Readiness	Latent (exogenous)	Perception that the bank has sufficient digital infrastructure, data quality, budgets, and specialized staff to implement AI.	5-point Likert items
RE	Regulatory Environment	Latent (exogenous)	Perceived clarity, adequacy, and supportiveness of Qatar's regulations for AI and FinTech, including AI guidelines and sandbox support.	5-point Likert items
FP	Fairness Perception	Latent (mediating)	Employee perception that AI systems produce fair, unbiased, and non-discriminatory outcomes.	5-point Likert items
PT	Perceived Trust in AI systems	Latent (mediating)	Degree of trust that AI tools in the bank are reliable, transparent, secure, and properly supervised by humans and regulators.	5-point Likert items
IA	Intention to Adopt AI	Latent (endogenous)	Behavioral intention of employees and their institutions to accept, use, and expand AI applications in banking operations.	5-point Likert items
BANK_TYPE	Bank type	Control	Type of institution where the respondent works: conventional, Islamic, foreign, or FinTech/digital bank.	1 = Conventional, 2 = Islamic, 3 = Foreign, 4 = FinTech/Digital
AI_EXP	AI exposure level	Control	Respondent's exposure to AI tools in daily work.	0 = No AI, 1 = Basic AI, 2 = Advanced AI
ROLE	Job role	Control	Main functional role: technology/IT, risk/compliance, operations/customer service, management.	Categorical, dummy variables in analysis
EXP_YRS	Banking experience (years)	Control	Number of years the respondent has worked in the banking/financial sector.	Continuous or grouped
GENDER	Gender	Control	Respondent's gender, if collected.	1 = Male, 2 = Female
AGE	Age	Control	Respondent's age or age group.	Continuous or grouped