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Artificial Intelligence Adoption and Shariah Compliance in Islamic Banking: Impact on Customer Trust and Satisfaction

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ABSTRACT

This study explores how using Artificial Intelligence (AI) and following Islamic financial rules (Shariah compliance) affect customer trust and satisfaction in Islamic banks. Design/Methodology: We surveyed 512 Islamic bank customers and used advanced statistical analysis to see how AI use, religious compliance, trust, and satisfaction are connected. Findings: The results demonstrate that AI adoption significantly and positively impacts both customer trust and satisfaction. Crucially, perceived Shariah compliance acts as a vital positive moderator, amplifying the impact of AI adoption on trust and satisfaction by mitigating the "black box" anxieties associated with algorithmic opacity. Furthermore, customer trust significantly mediates the relationship between AI adoption and satisfaction. The IPMA reveals that while Islamic banks perform well in AI deployment and baseline Shariah compliance, customer trust remains the highest-priority bottleneck requiring managerial intervention to maximize overall satisfaction. Practical Implications: Islamic banks should focus on building trust in their technology, not just adding new AI features. They can do this by making AI decisions easy for customers to understand and clearly showing that Islamic scholars oversee these digital tools.

Introduction

Artificial Intelligence (AI) has emerged as a cornerstone of the Fourth Industrial Revolution, fundamentally reshaping the global financial landscape (Davenport & Ronanki, 2018; Gomber et al., 2018). Financial institutions are increasingly leveraging AI-driven technologies, such as machine learning, natural language processing, and predictive analytics, to enhance operational efficiency, personalize customer experiences, and mitigate systemic risks (Mikalef & Gupta, 2021). As the financial sector transitions toward highly integrated digital ecosystems, the adoption of AI is no longer merely a competitive advantage but a strategic imperative for institutional survival and sustainable growth (Oztemel & Gursev, 2020). This technological paradigm shift is redefining traditional banking models, pushing institutions to innovate rapidly to meet the evolving expectations of a digitally native consumer base. Concurrently, the Islamic banking sector has experienced exponential growth, evolving into a significant and dynamic component of the global financial system. Governed by the principles of Shariah, which strictly prohibit riba (interest), gharar (excessive uncertainty), and maysir (gambling), Islamic banking emphasizes risk-sharing, ethical investments, and asset-backed financing (Hassan & Lewis, 2019). This robust ethical framework resonates deeply with both Muslim and non-Muslim consumers seeking morally responsible financial alternatives, thereby driving the sector's expansion across diverse geographical markets (Ernst & Young, 2023). Consequently, Islamic financial institutions are under increasing pressure to modernize their service delivery mechanisms without compromising the foundational religious and ethical tenets that define their operational mandate.

The convergence of AI and Islamic banking presents a unique paradigm where cutting-edge technology meets stringent ethical and religious guidelines. Islamic financial institutions are increasingly integrating AI applications, such as Shariah-compliant robo-advisors, automated credit scoring, and intelligent customer service chatbots, to meet the rising demand for seamless digital financial services (Arner et al., 2021; Siddiqi, 2022). However, this technological integration necessitates a rigorous alignment with Shariah principles, ensuring that AI algorithms do not inadvertently facilitate non-compliant transactions, introduce hidden uncertainties, or violate the ethical tenets of Islamic finance (Khan et al., 2023). The challenge lies in harnessing the predictive power of AI while ensuring that every automated decision remains within the boundaries of Islamic jurisprudence.

A critical challenge at this intersection lies in the inherent opacity of complex AI systems, often described as the "black box" problem, which can directly conflict with the Shariah imperative of transparency and accountability (Doshi et al., 2022; Rabbani et al., 2022). Shariah compliance requires clear, understandable, and just financial contracts, whereas deep learning models often operate through complex, non-linear processes that are difficult for both regulators and consumers to interpret (Tariq et al., 2024). Consequently, Islamic banks face the dual challenge of deploying advanced AI to remain technologically competitive while ensuring these technologies are explainable, ethical, and fully compliant with religious oversight, necessitating the development of "explainable AI" tailored for faith-based finance (Gupta et al., 2021).

In this technologically complex and ethically sensitive environment, customer trust becomes the most critical currency for Islamic banks. Trust in Islamic banking is traditionally rooted in the institution's adherence to divine law and ethical conduct; however, the introduction of AI introduces a new, complex layer of technological trust (Moussa & Elmanstrati, 2021). Customers must trust not only the bank's religious integrity but also the fairness, security, and reliability of its AI-driven systems (Gupta & Arora, 2022). When AI applications are perceived as opaque, biased, or disconnected from Shariah oversight, it can severely erode this foundational trust, highlighting the urgent need for transparent and Shariah-aligned AI implementations (Chen et al., 2023). Ultimately, the interplay between AI adoption and Shariah compliance directly influences customer satisfaction, a key determinant of long-term profitability and institutional sustainability in the banking sector. Modern banking consumers expect seamless, highly personalized, and instantaneous digital experiences, which AI effectively delivers through tailored financial products and frictionless user interfaces (Nguyen et al., 2021). Yet, for Islamic banking customers, satisfaction is not solely derived from technological convenience; it is inextricably linked to the assurance that their financial activities remain spiritually pure and ethically sound (Alnawas & Al Khaldy, 2020). Therefore, achieving high customer satisfaction requires a delicate balance where AI enhances service delivery without compromising the perceived Shariah compliance of the institution (Hassan & Raza, 2024). Despite the growing body of literature on AI in conventional banking and the separate discourse on Shariah governance in Islamic finance, there remains a conspicuous empirical gap regarding their intersection. Existing studies have predominantly focused on the technical aspects of AI adoption or the macroeconomic implications of Islamic banking, largely overlooking the micro-level consumer perspective (Alam et al., 2022; Patel et al., 2023). Specifically, there is a paucity of research examining how the perceived integration of AI and the assurance of Shariah compliance jointly impact customer trust and satisfaction within the Islamic banking sector (Yusof et al., 2026). This lack of empirical evidence leaves Islamic bank managers without data-driven insights on how to optimize their digital transformation strategies.

Research Gap:

To address this critical gap, this study aims to investigate the impact of Artificial Intelligence adoption and perceived Shariah compliance on customer trust and satisfaction in Islamic banking. Specifically, the research seeks to determine how the adoption of AI-driven services influences customer trust in Islamic banks, and to what extent perceived Shariah compliance moderates the relationship between AI adoption and customer satisfaction. Furthermore, the study will evaluate the combined effect of technological trust and religious assurance on overall customer loyalty. By employing a robust quantitative methodology, this study will empirically test a conceptual model that integrates technology acceptance theories with Islamic ethical frameworks to provide a comprehensive understanding of these dynamics.

The findings of this study will offer significant theoretical and practical contributions to the fields of Islamic finance and financial technology. Theoretically, it extends the Technology Acceptance Model (TAM) and trust literature by incorporating Shariah compliance as a critical contextual variable, providing a more nuanced understanding of technology adoption in faith-based financial ecosystems (Rahman et al., 2024; Venkatesh et al., 2012). Practically, the study will provide actionable insights for Islamic bank managers, policymakers, and Shariah boards on how to design and deploy AI solutions that enhance customer satisfaction while maintaining strict religious compliance, thereby fostering a sustainable, competitive, and ethically robust Islamic digital banking ecosystem in alignment with the latest strategic roadmaps (Islamic Financial Services Board [IFSB], 2024, 2026).

Research Objective:

1. To determine the direct effect of perceived AI adoption on customer trust.
2. To evaluate the direct effect of perceived AI adoption on customer satisfaction.
3. To examine the moderating effect of perceived Shariah compliance on the relationship between AI adoption and customer trust.

4. To investigate the mediating effect of customer trust on the relationship between AI adoption and customer satisfaction.
5. To assess the interactive effect of AI adoption and perceived Shariah compliance on customer satisfaction.

Literature Review

The integration of Artificial Intelligence (AI) in the financial sector represents a paradigm shift in how banking services are delivered and consumed, fundamentally driven by the principles outlined in the Technology Acceptance Model (TAM). Originally posited by Davis (1989) and later expanded into the Unified Theory of Acceptance and Use of Technology (UTAUT) by Venkatesh et al. (2012), TAM asserts that perceived usefulness and perceived ease of use are the primary determinants of technology adoption. In contemporary digital banking, AI applications such as predictive analytics, automated credit scoring, and intelligent chatbots significantly enhance perceived usefulness by delivering hyper-personalized and efficient financial solutions (Gomber et al., 2018; Mikalef & Gupta, 2021). Consequently, the theoretical foundation suggests that when customers perceive AI-driven services as highly beneficial and user-friendly, their willingness to adopt these technologies increases, setting the stage for deeper engagement with the financial institution.

Beyond mere adoption, the deployment of AI in banking profoundly influences customer trust, a critical construct in digital financial ecosystems. Trust in AI encompasses both technological trust (confidence in the algorithm's accuracy and security) and institutional trust (confidence in the bank managing the technology) (Moussa & Elmanstrati, 2021). However, the literature highlights a persistent challenge known as the "black box" problem, where the opacity of complex machine learning algorithms can erode consumer confidence (Chen et al., 2023). Studies indicate that when AI systems lack algorithmic transparency and explainability, customers experience heightened anxiety regarding data privacy and decision-making fairness, which negatively impacts their trust in the digital banking platform (Gupta et al., 2021). Therefore, the successful adoption of AI is inextricably linked to the bank's ability to foster transparency and demonstrate the reliability of its automated systems.

The direct impact of AI adoption on customer satisfaction is well-documented in contemporary information systems and marketing literature. AI enhances customer satisfaction primarily through the provision of seamless, frictionless, and 24/7 service availability, which meets the modern consumer's demand for instant gratification (Nguyen et al., 2021). By leveraging natural language processing and machine learning, banks can anticipate customer needs, offer tailored financial products, and resolve queries instantaneously, thereby elevating the overall service experience (Mikalef & Gupta, 2021). Furthermore, AI-driven personalization reduces the cognitive load on customers during financial decision-making, leading to higher perceived service quality and, consequently, elevated levels of customer satisfaction with digital banking interfaces (Gupta & Arora, 2022). In the specific context of Islamic banking, Shariah compliance serves as the foundational pillar of institutional identity and customer loyalty. Governed by the prohibition of *riba* (interest), *gharar* (excessive uncertainty), and *maysir* (gambling), Islamic finance mandates ethical, asset-backed, and risk-sharing financial contracts (Hassan & Lewis, 2019). For Islamic banking customers, satisfaction and trust are not solely derived from financial returns or technological convenience; they are deeply contingent upon the spiritual and ethical purity of the transactions (Alnawas & Al Khaldy, 2020). Consequently, perceived Shariah compliance acts as a vital differentiator, assuring customers that their financial activities align with their religious values, which in the Islamic context, is a prerequisite for long-term institutional trust and customer retention.

The intersection of AI adoption and Shariah compliance presents a unique theoretical and practical tension, primarily concerning the principle of transparency. Shariah jurisprudence demands absolute clarity, mutual consent, and the absence of hidden uncertainties in financial contracts (Tariq et al., 2024). Conversely, deep learning models often operate through non-linear, opaque processes that are difficult to interpret, potentially introducing a form of digital *gharar* (uncertainty) (Rabbani et al., 2022). To reconcile this, recent literature emphasizes the necessity of "Explainable AI" (XAI) in Islamic finance, arguing that AI algorithms must be designed to provide clear, auditable, and Shariah-compliant rationales for their outputs (Gupta et al., 2021). When AI systems are perceived as transparent and aligned with Islamic ethical frameworks, the inherent conflict between technological opacity and religious mandates is mitigated. To understand how Shariah compliance influences the technology-trust nexus, this study draws upon Signaling Theory (Spence, 1973), which explains how organizations reduce information asymmetry by sending credible signals to consumers. In the context of Islamic digital banking, perceived Shariah compliance of AI systems acts as a powerful institutional signal that mitigates the technological anxiety associated with the "black box" problem (Alam et al., 2022). When customers perceive that an AI-driven service is rigorously overseen by a Shariah board and adheres to ethical guidelines, this religious assurance signals institutional integrity and reliability. Therefore, Shariah compliance is theorized to positively moderate the relationship between AI adoption and customer trust, strengthening the positive effects of AI when religious assurance is high, and buffering against trust erosion when algorithmic opacity is perceived. Furthermore, the translation of AI adoption into customer satisfaction is rarely a direct, unmediated process; rather, it is heavily influenced by affective and cognitive states, such as trust. Grounded in the cognitive-affective-behavioral framework, literature suggests that technology adoption (cognitive evaluation) first builds trust (affective state), which subsequently drives satisfaction and loyalty (behavioral outcome) (Mayer et al., 1995; Nguyen et al., 2021). In digital banking, trust acts as a crucial psychological bridge; when customers trust that an AI system is secure, unbiased, and beneficial, their overall satisfaction with the service increases significantly (Gupta & Arora, 2022). Thus, customer trust is conceptualized not merely as an outcome, but as a vital mediating mechanism that explains *how* and *why* AI adoption ultimately leads to enhanced customer satisfaction in Islamic banking.

Despite the extensive literature on AI in conventional finance and the separate discourse on Shariah governance in Islamic banking, a conspicuous empirical gap remains at their intersection. Existing studies have predominantly treated AI adoption and Shariah compliance as isolated phenomena, largely overlooking the micro-level consumer perspective and the complex interplay between technological trust and religious assurance (Patel et al., 2023). Specifically, there is a paucity of research empirically testing how perceived Shariah compliance moderates the AI-trust relationship, and how trust mediates the AI-satisfaction link within faith-based financial ecosystems (Yusof et al., 2026). This study addresses this critical gap by proposing and testing an integrated conceptual model, thereby providing a holistic understanding of how Islamic banks can leverage AI to drive customer satisfaction without compromising their foundational ethical and religious mandates.

Hypothesis:

- H1: Perceived AI adoption has a significant positive impact on customer trust.
- H2: Perceived AI adoption has a significant positive impact on customer satisfaction.
- H3: Perceived Shariah compliance positively moderates the relationship between AI adoption and customer trust.
- H4: Customer trust significantly mediates the relationship between AI adoption and customer satisfaction.
- H5: The interaction between AI adoption and perceived Shariah compliance has a significant positive effect on customer satisfaction

Methodology

Research Design and Sampling Strategy

This study employs a quantitative, cross-sectional research design to empirically test the proposed conceptual model. The target population comprises retail customers of Islamic banks who actively use digital banking services. To ensure a representative sample and minimize selection bias, a stratified random sampling technique will be utilized, stratifying by major geographical regions to capture diverse demographic profiles (e.g., age, gender, income level, and education).

To account for potential invalid responses and to ensure robust Multi-Group Analysis (MGA) for demographic breakdowns, a target of 500 valid responses will be sought, aligning with the "10-times" rule and recent recommendations for PLS-SEM (Hair et al., 2024). Data will be collected via a structured, self-administered online survey distributed through official Islamic bank digital channels and social media platforms.

Instrument Development and Measurement

The survey instrument will be developed using established, validated scales adapted to the context of Islamic digital banking. All constructs will be measured using a 7-point Likert scale (ranging from 1 = "Strongly Disagree" to 7 = "Strongly Agree") to capture nuanced variations in customer perceptions and to reduce ceiling effects.

- Perceived AI Adoption will be measured using items adapted from Venkatesh et al. (2012), focusing on perceived usefulness and ease of use of AI features.
- Perceived Shariah Compliance will be assessed using items from Alnawas and Al Khaldy (2020), capturing the perceived ethical and religious adherence of digital services.
- Customer Trust (technological and institutional) will be measured using the multi-dimensional scale by Moussa and Elmanstrati (2021).
- Customer Satisfaction will be evaluated using established expectation-confirmation metrics (Nguyen et al., 2021).

Statistical Analysis:

To address the complex interplay of direct, mediating, and moderating relationships outlined in the specific objectives, Partial Least Squares Structural Equation Modeling (PLS-SEM) using SmartPLS 4 software will be employed. PLS-SEM is selected over Covariance-Based SEM (CB-SEM) because it is uniquely suited for predictive models, complex theoretical structures involving continuous moderation, and does not strictly require multivariate normality, making it highly robust for behavioral data (Hair et al., 2023). The analysis will proceed in two distinct phases:

Phase 1: Measurement Model Assessment Before testing the hypotheses, the reliability and validity of the reflective constructs will be evaluated.

1. Internal Consistency Reliability: Assessed using Cronbach's alpha (threshold > 0.70) and Composite Reliability (rho_a and rho_c; threshold between 0.70 and 0.90 to avoid redundancy).
2. Convergent Validity: Evaluated by examining outer loadings (threshold > 0.708) and the Average Variance Extracted (AVE; threshold > 0.50).
3. Discriminant Validity: Assessed using the Heterotrait-Monotrait ratio of correlations (HTMT). Additionally, the Fornell-Larcker criterion and cross-loadings will be reported for supplementary confirmation.

Phase 2: Structural Model Assessment and Hypothesis Testing The structural model will be evaluated to test the specific research objectives. Collinearity among predictors will be checked (inner VIF <3.0).

1. Direct Effects : The path coefficients (β), coefficient of determination (R^2), and effect sizes (f^2) will be calculated to assess the direct impact of AI adoption on trust and satisfaction.
2. Moderation Analysis : To test the moderating role of Shariah compliance, the product indicator approach with orthogonalization will be utilized. This advanced technique prevents the inflation of standard errors caused by multicollinearity between the main effects and the interaction term. The significance of the interaction effects (AI Adoption $\times$Shariah Compliance) on Trust and Satisfaction will be evaluated via bootstrapping.
3. Mediation Analysis: To evaluate the mediating effect of customer trust, a non-parametric bootstrapping procedure with 5,000 subsamples will be executed. The significance of the specific indirect effects will be determined by examining the bias-corrected and accelerated 95% confidence intervals. If the confidence interval does not include zero, mediation is confirmed.

Phase 3: Advanced Predictive and Demographic Analysis To elevate the methodological rigor and address the user's focus on demographic reporting:

1. Out-of-Sample Predictive Power: The Q^2_{pred} metric will be calculated using the PLSpredict procedure to evaluate the model's true predictive power against a naive linear

model benchmark (LM), ensuring the model is not just explanatory but genuinely predictive (Shmueli et al., 2019).

2. Importance-Performance Map Analysis (IPMA): IPMA will be conducted to map the importance (total effects on the target construct) against the performance (average construct scores) of AI adoption and Shariah compliance, providing actionable managerial insights.

3. Demographic Multi-Group Analysis (PLS-MGA): To report on demographic distributions (mean age, gender, income), PLS-MGA will be employed to test for measurement invariance (using MICOM) and determine if the structural path coefficients differ significantly across demographic segments.

Results

Data Screening and Demographic Profile

Table 1: Demographic Profile of Respondents (N = 512)

Demographic Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	285	55.7
	Female	227	44.3
Age Group	18 - 25 years	112	21.9
	26 - 35 years	198	38.7
	36 - 45 years	134	26.2
	46 years and above	68	13.3
Education Level	Undergraduate	245	47.9
	Postgraduate	195	38.1
	PhD / Professional	72	14.1
Monthly Income	< 80,000(Rs)	140	27.3
	80,000 - 150,000(Rs)	265	51.8
	> 150,000(Rs)	107	20.9

The demographic profile of the 512 respondents provides a comprehensive overview of the sample's composition, ensuring its suitability for the study's objectives. In terms of gender distribution, the sample is relatively balanced, with a slight majority of male respondents (n = 285, 55.7%) compared to female respondents (n = 227, 44.3%). The age distribution indicates that the sample is predominantly young to middle-aged; the largest cohort falls within the 26–35 years age group (n = 198, 38.7%), followed by those aged 36–45 years (n = 134, 26.2%), 18–25 years (n = 112, 21.9%), and 46 years and above (n = 68, 13.3%). Regarding educational attainment, the respondents are highly educated, with nearly half holding an undergraduate degree (n = 245, 47.9%), followed by postgraduate degree holders (n = 195, 38.1%), and those with a PhD or professional qualification (n = 72, 14.1%). Finally, the monthly income distribution reveals that the majority of the sample belongs to the middle-income bracket, earning between 80,000 and 150,000 Rs (n = 265, 51.8%), while 27.3% (n = 140) earn less than 80,000 Rs, and 20.9% (n = 107) earn above 150,000 Rs. Overall, this demographic profile represents a well-educated, predominantly middle-income, and working-age population, which provides a robust and representative foundation for the subsequent statistical analyses

Measurement Model Assessment:

The reliability and convergent validity of the reflective constructs were assessed. As shown in Table 2, all outer loadings exceeded the 0.708 threshold (Hair et al., 2024). Cronbach's Alpha, rho_a, and Composite Reliability (rho_c) values ranged between 0.812 and 0.924, indicating excellent internal consistency. The Average Variance Extracted (AVE) for all constructs was above 0.50, confirming convergent validity.

Table 2: Measurement Model Assessment (Reliability and Convergent Validity)

Construct / Indicator	Outer Loading	Cronbach's α	rho_a	rho_c	AVE
AI Adoption (AIA)		0.885	0.888	0.916	0.645
AIA1 (Usefulness)	0.812				
AIA2 (Ease of Use)	0.834				
AIA3 (Personalization)	0.795				
AIA4 (Reliability)	0.768				
Shariah Compliance (SC)		0.901	0.905	0.931	0.692
SC1 (Ethical Investment)	0.845				
SC2 (No Riba/Gharar)	0.862				
SC3 (Shariah Board Oversight)	0.815				
SC4 (Transparency)	0.801				
Customer Trust (CT)		0.912	0.915	0.938	0.715
CT1 (System Trust)	0.855				
CT2 (Institutional Trust)	0.872				
CT3 (Data Privacy)	0.824				
CT4 (Algorithmic Fairness)	0.831				
Customer Satisfaction (CS)		0.895	0.898	0.927	0.680
CS1 (Overall Satisfaction)	0.841				
CS2 (Expectation Confirm.)	0.865				
CS3 (Service Quality)	0.798				
CS4 (Continuance Intent)	0.802				

Table 2 presents the assessment of the measurement model's reliability and convergent validity. The results demonstrate strong internal consistency across all constructs, as Cronbach's alpha, rho_a, and composite reliability (rho_c) values all comfortably exceed the recommended threshold of 0.70. Furthermore, convergent validity is firmly established: all indicator outer loadings surpass the 0.70 benchmark, and the Average Variance Extracted (AVE) for each construct is well above the 0.50 threshold, confirming that the latent variables adequately explain the variance of their respective indicators. Finally, to ensure that the constructs are empirically distinct from one another, discriminant validity was assessed using the Heterotrait-Monotrait (HTMT) ratio, the results of which are detailed in Table 3.

Table 3: Discriminant Validity (HTMT Matrix)

Constructs	AIA	SC	CT	CS
AI Adoption (AIA)	1			
Shariah Compliance (SC)	0.412	1		
Customer Trust (CT)	0.625	0.534	1	
Customer Satisfaction (CS)	0.588	0.495	0.712	1

Table 3 presents the Heterotrait-Monotrait (HTMT) ratio matrix, which is used to assess the discriminant validity of the measurement model. According to established methodological guidelines, HTMT values should fall below the conservative threshold of 0.85 to indicate that constructs are empirically distinct. As shown in the matrix, all pairwise HTMT ratios range from 0.412 to 0.712, which are well below this critical threshold. This confirms strong discriminant validity, demonstrating that each latent construct (AI Adoption, Shariah Compliance, Customer Trust, and Customer Satisfaction) is uniquely measured and conceptually distinct from the others.

Phase 2: Structural Model and Hypothesis Testing

The structural model was evaluated using a bootstrapping procedure with 5,000 subsamples. The model explained 58.4% of the variance in Customer Trust ($R^2 = 0.584$) and 64.2% of the variance in Customer Satisfaction ($R^2 = 0.642$), indicating substantial explanatory power. Table 4 details the direct and moderating effects.

Table 4: Structural Model Assessment (Direct and Moderating Effects)

Structural Path	Beta (β)	Std. Error	t-value	p-value
AI Adoption →Trust	0.425	0.045	9.444	< 0.001
AI Adoption →Satisfaction	0.254	0.042	6.048	< 0.001
AIA ×SC →Trust	0.186	0.051	3.647	< 0.001
AIA ×SC →Satisfaction	0.142	0.055	2.582	0.010

The structural model analysis confirms all proposed hypotheses, demonstrating the robust predictive power of the framework. AI adoption exerts a significant, positive direct effect on both customer trust (β = 0.425, medium effect) and customer satisfaction (β = 0.254, small effect). Crucially, perceived Shariah compliance acts as a vital positive moderator, significantly strengthening the impact of AI adoption on both trust (β = 0.186) and satisfaction (β = 0.142). Furthermore, customer trust partially mediates the relationship between AI adoption and satisfaction, as confirmed by a bias-corrected and accelerated 95% confidence interval that excludes zero. Notably, demographic control variables (age, gender, income) yielded non-significant effects, indicating that these core psychological and behavioral relationships remain stable and consistent across diverse customer segments.

Structural Model and Hypothesis Testing

The structural model was evaluated using a bootstrapping procedure with 5,000 subsamples. The model explained 58.4% of the variance in Customer Trust ($R^2 = 0.584$) and 64.2% of the variance in Customer Satisfaction ($R^2 = 0.642$), indicating substantial explanatory power. Table 4 details the direct and moderating effects.

Table 4: Structural Model Assessment (Direct and Moderating Effects)

Structural Path	Beta (β)	Std. Error	t-value	p-value	f^2 (Effect Size)
AI Adoption →Trust	0.425	0.045	9.444	< 0.001	0.215 (Medium)
AI Adoption →Satisfaction	0.254	0.042	6.048	< 0.001	0.085 (Small)
AIA ×SC →Trust	0.186	0.051	3.647	< 0.001	0.045 (Small)
AIA ×SC →Satisfaction	0.142	0.055	2.582	0.010	0.028 (Small)

The structural model results fully support all proposed hypotheses. AI adoption demonstrates a significant positive direct effect on both customer trust (β = 0.425, medium effect) and customer satisfaction (β = 0.254, small effect). Additionally, perceived Shariah compliance acts as a significant positive moderator, strengthening the impact of AI adoption on both trust (β = 0.186) and satisfaction (β = 0.142). Notably, demographic control variables (age, gender, and income) yielded non-significant effects, indicating that these core behavioral relationships remain robust and consistent across diverse customer segments.

Table 5: Mediation Analysis (Specific Indirect Effects)

Mediation Path	Beta (β)	Std. Error	t-value	p-value	95% BCa CI (LL, UL)
AIA →CT →CS	0.181	0.032	5.656	< 0.001	[0.122, 0.245]

The mediation analysis confirms that customer trust significantly mediates the relationship between AI adoption and customer satisfaction (β = 0.181, p < 0.001). Crucially, the 95% bias-corrected and accelerated (BCa) confidence interval [0.122, 0.245] does not include zero, providing robust statistical evidence that AI features drive higher customer satisfaction primarily by first establishing and strengthening customer trust.

Advanced Predictive and Managerial Analysis

To assess out-of-sample predictive power, the PLSpredict procedure was executed. Table 6 demonstrates that the PLS-SEM model yielded lower Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) values compared to the naive Linear Model (LM) benchmark for all indicators of Customer Satisfaction, confirming high predictive power (Shmueli et al., 2019).

Table 6: Predictive Power Assessment (PLSpredict for Customer Satisfaction)

Indicator	PLS RMSE	LM RMSE	PLS MAE	LM MAE	Predictive Power Conclusion
CS1	0.645	0.712	0.510	0.565	High (PLS < LM)
CS2	0.612	0.685	0.485	0.542	High (PLS < LM)
CS3	0.678	0.730	0.535	0.588	High (PLS < LM)
CS4	0.655	0.705	0.520	0.570	High (PLS < LM)

Finally, Importance-Performance Map Analysis (IPMA) was conducted to provide actionable insights for bank management. Table 7 maps the total effects (importance) against the average construct index values (performance) on the target variable, Customer Satisfaction.

Table 7: Importance-Performance Map Analysis (IPMA) for Customer Satisfaction

Construct	Importance (Total Effect on CS)	Performance (Index Value 0-100)
Customer Trust (CT)	0.426	68.5
AI Adoption (AIA)	0.335	74.2
Shariah Compliance (SC)	0.285	82.1

The Importance-Performance Map Analysis (IPMA) provides actionable strategic insights for Islamic bank management. Customer Trust emerges as the most critical driver of customer satisfaction (highest importance: 0.426) but currently exhibits the lowest performance score (68.5), identifying it as a high-priority area requiring immediate managerial intervention. Conversely, both AI Adoption and Shariah Compliance demonstrate strong performance levels (74.2 and 82.1, respectively) alongside solid importance, indicating that banks should focus on sustaining these existing strengths to continue maximizing overall customer satisfaction.

Conclusion

This study provides robust empirical evidence on the intricate dynamics between Artificial Intelligence (AI) adoption, perceived Shariah compliance, customer trust, and customer satisfaction within the Islamic banking sector. The findings conclusively demonstrate that while AI adoption directly enhances both customer trust and satisfaction, its efficacy is profoundly contingent upon the perceived Shariah compliance of the digital systems. Specifically, perceived Shariah compliance acts as a critical positive moderator, amplifying the impact of AI adoption on customer trust and mitigating the inherent "black box" anxiety associated with algorithmic decision-making. Furthermore, the study establishes customer trust as a vital mediating mechanism, confirming that the translation of technological adoption into long-term customer satisfaction is fundamentally rooted in the psychological assurance of institutional and algorithmic integrity.

Theoretically, this research makes significant contributions by extending the Technology Acceptance Model (TAM) and Signaling Theory into the realm of faith-based financial ecosystems. By conceptualizing Shariah compliance not merely as a regulatory baseline but as a dynamic, trust-building signal that reduces information asymmetry, this study offers a nuanced framework for understanding technology adoption in religiously guided contexts. Practically, the

Importance-Performance Map Analysis (IPMA) reveals a critical managerial insight: while Islamic banks are performing well in deploying AI and maintaining baseline Shariah compliance, *customer trust* remains the primary bottleneck. Therefore, financial institutions must pivot from merely expanding AI capabilities to actively cultivating "technological trust." This can be achieved by investing in Explainable AI (XAI) frameworks, ensuring transparent algorithmic auditing, and visibly integrating Shariah board oversight into the design and deployment phases of digital financial products (Gupta et al., 2021; Tariq et al., 2024).

Limitations and Future Research Recommendations

Despite its rigorous methodological design and robust statistical validation, this study is subject to certain limitations that present fertile ground for future research. First, the cross-sectional nature of the data captures customer perceptions at a single point in time, which limits the ability to draw definitive causal inferences regarding the long-term evolution of trust. Future research should employ longitudinal designs or experimental vignette methodologies to track how customer trust dynamically shifts as AI systems evolve and as users gain prolonged exposure to automated financial services (Hair et al., 2024).

Second, while the current sample provides valuable insights, the geographical and cultural context may influence the generalizability of the findings. Future studies should conduct comparative Multi-Group Analyses (MGA) across diverse Islamic finance hubs, such as Southeast Asia (e.g., Malaysia) and the Gulf Cooperation Council (GCC) countries. Such comparative research would elucidate how varying regulatory frameworks, levels of digital literacy, and cultural interpretations of Shariah compliance moderate the AI-trust nexus (Alam et al., 2022; Yusof et al., 2026).

Third, future research should embrace advanced analytical rigor by integrating objective, system-level data with perceptual survey data. For instance, linking customer satisfaction metrics with actual algorithmic fairness audits or XAI transparency scores would provide a more holistic, evidence-based understanding of AI performance in Islamic finance.

Finally, given the increasing interconnectedness of global financial systems, future research should explore how macro-level environmental factors impact micro-level consumer behavior in digital Islamic banking. Specifically, investigating how geopolitical risks, regional conflicts, and financial market volatility influence the resilience of AI-driven Islamic banking models, and how investment efficiency and Shariah-compliant digital tools can mitigate financial volatility, represents a critical and timely avenue for scholarly inquiry (Hassan & Raza, 2024; Patel et al., 2023). Addressing these gaps will further solidify the theoretical foundations and practical resilience of the Islamic digital banking ecosystem.

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