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Artificial Intelligence Integration and Financial Literacy Enhancement in Jordanian Islamic Banks: The Moderating Role of Customer Trust

Aissar Abdelqader Alrababeh
School of Management, Universiti Sains Malaysia (USM), 11800 Penang, Malaysia
Email: Aissar.alrababeh@gmail.com

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Abstract
Jordan's Islamic banking sector has deployed AI-enabled digital services at a pace that has outrun systematic evidence on what those tools actually do to customer financial understanding. This paper examines that question empirically. Using survey data from 312 active digital banking customers across three licensed Jordanian Islamic banks, collected between September and November 2024, we test whether perceived AI integration is positively associated with financial literacy a construct that, in Islamic banking, spans both general financial knowledge and understanding of Sharia-specific product structures. We also ask whether customer trust moderates this relationship: specifically, whether the association between AI integration and literacy is stronger among customers who trust both the technical reliability and the religious legitimacy of their bank's AI tools. Data were analysed using PLS-SEM in SmartPLS 4, with Full Collinearity VIF diagnostics for common method bias and two-stage orthogonalisation for moderation. A positive association between AI integration and financial literacy emerged ($\beta = 0.42$, $p < .001$, $f^2 = 0.18$), and customer trust significantly strengthened that association ($\beta = 0.14$, $p = .012$). The model explains 43 per cent of the variance in financial literacy. Digital self-efficacy was an independent positive predictor, signalling that AI's educational benefits are not uniformly distributed. We interpret these results as associations rather than causal effects, and discuss what they mean for how Jordanian Islamic banks design their digital tools and how the Central Bank of Jordan frames its financial inclusion strategy.
Keywords: Artificial Intelligence, Financial Literacy, Islamic Banking, Customer Trust, Jordan, Sharia Compliance, PLS-Sem, Digital Banking

Introduction

Every day, across the branches and mobile screens of Jordan's Islamic banks, customers complete transactions they do not fully understand. They sign *Murabaha* financing agreements, renew *Mudaraba* savings accounts, and navigate digital interfaces that process significant portions of their financial lives, often without knowing what the terms mean, why the product is structured the way it is, or what rights they hold when something goes wrong. This is not a marginal concern. It sits at the centre of what Islamic banking is supposed to be, and what it risks failing to be when financial literacy is absent.

Financial literacy, broadly understood as the combination of knowledge, skills, and attitudes that enables individuals to make responsible and informed financial decisions, has been consistently linked to better outcomes across every dimension of personal economic life. Individuals with stronger financial knowledge save more reliably, take on debt more carefully, plan earlier for retirement, and demonstrate greater resilience during economic shocks (Lusardi & Mitchell, 2014). At the national level, higher financial literacy rates are associated with more efficient capital allocation, reduced household debt burdens, and more inclusive financial systems, gains that matter most in economies where access to formal financial services is still unevenly distributed (World Bank, 2022). It is for this reason that financial education has shifted, in the thinking of policymakers and regulators worldwide, from an optional public service to a foundational pillar of financial inclusion strategy.

In Islamic banking, the literacy challenge carries an additional layer of complexity that has no real equivalent in conventional finance. Customers of Sharia-compliant institutions are not simply asked to understand interest rates or repayment schedules. They are asked to understand a set of religious and legal principles that shape the design of every product they use. The prohibition of *riba*, the requirement to avoid *gharar*, the profit-sharing logic of *Mudaraba*, the ownership-transfer mechanism that distinguishes *Murabaha* from a straightforward interest-bearing loan: these are not concepts that most retail banking customers absorb passively or intuitively (Iqbal & Molyneux, 2005). A customer may hold sincere religious trust in their bank while being entirely unable to explain how profit is calculated on their savings account, or what their exposure is under a financing contract they signed without reading carefully. That distance between religious confidence and product comprehension is not merely a consumer protection concern. It has a bearing on the Sharia validity of the transactions themselves, since a contract entered without genuine informed understanding occupies a legally uncertain position in Islamic commercial law regardless of how carefully its structure has been designed (Iqbal & Mirakhor, 2011). Beck et al. (2013) observed that Islamic banks carry a communication burden that their conventional counterparts do not: they must explain not only what a product costs, but why it takes the form it does, and why that form matters from a religious standpoint. Meeting that burden requires customers who are capable of receiving and processing the explanation.

Jordan makes this challenge both concrete and urgent. Three fully licensed Islamic banks serve the retail market, namely Jordan Islamic Bank, Safwa Islamic Bank, and Jordan Dubai Islamic Bank, operating within a regulatory environment in which the Central Bank of Jordan has made digital financial services a central pillar of its national financial inclusion agenda (Central Bank of Jordan, 2023). Smartphone penetration is high among urban working-age adults, and the shift toward mobile-first banking has accelerated. At the same time, Jordan sits within a regional context that presents serious cause for concern: the Middle East and North Africa consistently records among the lowest financial literacy scores in global comparative surveys, with fewer than one in four adults reaching the standard knowledge benchmarks used by major international assessments (Klapper, Lusardi, & van Oudheusden, 2015). Sector reports and survey data suggest that Jordanian Islamic bank customers follow a pattern that is familiar across the region, namely strong religious trust in their institution combined with significant gaps in their practical understanding of the products they hold (World Bank, 2022). The gap is well documented, it carries real consequences for customers and institutions alike, and there is no evidence that it is closing without deliberate intervention.

Artificial intelligence has emerged, in this context, as a technology that many within the banking sector believe capable of serving as that intervention. Jordanian Islamic banks have invested substantially in AI-enabled tools embedded across their digital service environments, including real-time chatbots, personalised advisory features, automated product-explanation tools, and intelligent budgeting functions built into mobile applications (Rabbani et al., 2020; Zouari & Abdelhedi, 2021). The appeal of these tools as financial education mechanisms is not difficult to understand. A well-designed AI system is interactive in a way that a printed disclosure document cannot be. It is available at the moment a customer actually needs clarification rather than days before or after a transaction. It can, in principle, tailor the depth and language of an explanation to the individual asking the question. And it removes the social friction that sometimes prevents customers from asking what they fear may be an obvious question in front of a human advisor. For customers who are navigating the conceptual complexity of Islamic financial contracts, these are not trivial advantages.

The importance of examining this question extends well beyond academic interest. Bank managers and digital product teams need to know whether investment in AI tools produces genuine educational returns for customers, or whether improvements in efficiency and satisfaction scores mask unchanged or declining product comprehension. If AI tools do support literacy development, they deserve to be designed with that function in mind, evaluated against it, and positioned accordingly in customer communications. If they do not, or if their benefits are concentrated among customers who are already digitally capable and financially informed, then banks and regulators need to know that too, so that AI deployment does not substitute for the structured financial education programmes that remain necessary. For the Central Bank of Jordan specifically, this question has policy significance: whether digital banking expansion qualifies as a financial literacy strategy within the National Financial Inclusion Framework, or whether it addresses access and convenience without meaningfully closing knowledge gaps, shapes how resources and regulatory attention should be allocated (Central Bank of Jordan, 2023). For customers with limited digital experience, lower income levels, or residence outside major urban centres, the stakes are more personal. The answer determines whether the technology being rolled out in their name is genuinely working for them.

What the existing literature offers on this question is surprisingly thin. Studies in the Islamic fintech space have tended to focus on the determinants of AI adoption (Rabbani et al., 2020), on efficiency gains from AI implementation (Hassan & Aliyu, 2018), or on digital self-efficacy as a condition that precedes technology use rather than as an outcome shaped by it (Zouari & Abdelhedi, 2021). The question of what happens to a customer's financial understanding after they begin using AI-enabled banking tools has received little systematic attention. This gap is compounded by a legitimate reason for caution about optimistic assumptions. The algorithmic complexity that gives AI tools their power also makes them opaque, and opacity conflicts with the transparency that Islamic financial transactions are required to embody

(Hassan & Aliyu, 2018). There is nothing automatic about the translation from AI interaction to genuine understanding. A customer can complete a transaction through an intelligent interface faster and more smoothly than ever before while grasping its content less well than they would have through a slower, more effortful human exchange. The efficiency of the interaction may come at the cost of the reflection that learning requires.

This study examines whether and under what conditions AI integration in Islamic banking is associated with improved financial literacy among customers, with particular attention to the role that customer trust plays in that relationship. Trust, as operationalised here, encompasses two dimensions: confidence in the technical accuracy and reliability of AI-based banking tools, and confidence in their consistency with Islamic principles (Gefen et al., 2003; Raza et al., 2019). The theoretical argument is that trust shapes not whether customers use AI tools, since usage is a separate question addressed by a well-established adoption literature, but how they engage with those tools once they are using them. A customer who trusts the religious and technical integrity of an AI-generated explanation is likely to read it carefully, ask follow-up questions, and carry something away from the interaction. A customer who is uncertain about either dimension is more likely to use the tool as a means of completing a transaction quickly and move on. Trust is therefore treated in this study not as an antecedent of adoption but as a moderator of the relationship between AI integration and literacy outcome, the condition that determines whether the educational potential of AI tools is realised or bypassed in practice.

The study draws on survey data from 312 active digital banking customers across three licensed Jordanian Islamic banks, collected between September and November 2024, and analyses those data using PLS-SEM with Full Collinearity VIF diagnostics and two-stage orthogonalised moderation testing. It contributes to the literature in three ways: by providing direct empirical evidence on the association between perceived AI integration and financial literacy in an Islamic banking setting; by introducing and testing customer trust as a theoretically grounded moderator of that association; and by employing a sufficiently rigorous methodological design to support confident interpretation and to serve as a replicable foundation for future research in this domain.

The paper is organised as follows. Section 2 reviews the relevant literature and develops the hypotheses. Section 3 describes the research design, sampling procedure, measurement instruments, and analytical approach. Section 4 presents the measurement and structural model results. Section 5 discusses the findings in relation to both theory and practice. Section 6 addresses the study's limitations and suggests directions for future research. Section 7 concludes.

Literature Review and Hypothesis Development

What Financial Literacy Means and Why It Matters

The concept of financial literacy is older than most fintech researchers give it credit for, and it has never had a single agreed definition. By now, though, most researchers work with a framework that treats literacy as having three components that reinforce each other: what a person knows about finance, what they can actually do with that knowledge in a real decision, and how they tend to approach financial choices whether they plan ahead, whether they are comfortable with uncertainty, whether they save or spend by default.

The evidence connecting financial literacy to outcomes is by now substantial. Individuals who score higher on literacy assessments save more for retirement, carry less high-cost debt, and demonstrate more diversified portfolio choices (Lusardi & Mitchell, 2014). At the population level, Klapper, Lusardi, and van Oudheusden (2015) found that fewer than one in three adults worldwide could be classified as financially literate using the S&P three-question benchmark, with the Middle East and North Africa scoring among the lowest regions in the survey. Jordan sits within that regional context, and its relatively low aggregate literacy rates combined with a banking sector that expects customers to navigate genuinely complex Islamic financial instruments create a particularly pressing need for effective financial education mechanisms. What is sometimes overlooked is that financial literacy is malleable. It is not a fixed cognitive trait but a learned capability that responds to environmental factors, including the quality of information environments that financial institutions create. That malleability is the reason this paper examines AI tools as a potential literacy mechanism rather than simply treating literacy as a demographic control variable.

The Specific Challenge of Islamic Financial Literacy

General financial literacy frameworks, developed largely in the context of conventional banking, do not map cleanly onto the Islamic banking context. Understanding a *Murabaha* contract requires customers to grasp something more than "the bank charges a fee for financing my purchase." It requires understanding why the bank takes legal ownership of the asset before selling it to the customer why that sequence of transactions is what makes the arrangement Sharia-compliant rather than a disguised loan, and how the profit margin differs from interest in both form and jurisprudential status (Iqbal & Mirakhor, 2011). Similarly, making an informed choice between a *Mudaraba* savings account and a conventional deposit account requires understanding profit-sharing ratios, the distribution of losses under different scenarios, and the bank's obligations as the managing partner.

Islamic commercial law adds a further dimension that has no real counterpart in conventional finance. The prohibition of *gharar* typically translated as excessive uncertainty or ambiguity extends beyond speculative financial instruments to cover informational asymmetries in contracts. A customer who signs a *Mudaraba* agreement without understanding how their returns will be calculated, or who accepts a *Musharaka* arrangement without knowing their liability exposure, has arguably participated in a transaction that sits in a legally ambiguous Sharia position (Iqbal & Mirakhor, 2011). For Islamic banks, financial literacy among customers is therefore not merely a matter of good commercial practice or consumer protection it has a direct bearing on whether the transactions they facilitate meet their own religious standards.

Beck et al. (2013) make the practical observation that Islamic banks face a communication challenge that conventional banks do not: they must not only explain the terms of their products but also explain why those terms are structured as they are, which requires an additional layer of educational effort. Against this backdrop, it is perhaps unsurprising that international data show a pattern of customers who trust their Islamic bank deeply on religious grounds but struggle to explain how their own products work (World Bank, 2022). Closing that gap between religious confidence and product comprehension is precisely the challenge that AI tools are expected to address.

AI in Banking: Promise and Limitation

The enthusiasm for AI in banking is not without empirical basis. Jagtiani and Lemieux (2019) document how machine learning tools have extended credit access to borrowers who would have been rejected by conventional scoring methods, partly by identifying creditworthiness signals in non-traditional data. Customer-facing AI tools chatbots, advisory engines, automated product explanations have the theoretical advantage of being available around the clock, infinitely patient, and capable of adjusting their explanations to individual customer needs. For financial literacy specifically, these features matter: a customer who feels embarrassed asking a human advisor to explain a contract term for the third time may find it easier to query an AI system.

The limitations are real, though. The same machine learning architectures that make AI tools powerful tend to make them opaque. A chatbot that recommends one product over another based on pattern matching across thousands of prior customer interactions cannot easily explain its reasoning in terms that a customer without technical training would find meaningful. Jagtiani and Lemieux (2019) note this tension in the lending context, where algorithmic outputs may be accurate without being interpretable. In Islamic banking, the problem is compounded: if an AI system generates a product recommendation through a process that neither the customer nor the bank's Sharia supervisors can fully trace, the tool may technically facilityate a compliant transaction while undermining the informed consent that Sharia requires.

Rabbani, Khan, and Thalassinos (2020) reviewed the rapidly expanding literature on Islamic fintech and found consistent evidence that technology improves efficiency and accessibility in Islamic banking, but they identified the gap between technology *adoption* and customer *comprehension* as a persistent blind spot. Most studies in this space measure whether customers use digital tools, not whether using them makes customers more knowledgeable. Our study is a direct response to that gap.

Trust and the Sharia Dimension

Trust in digital financial services has been conceptualised and measured in a variety of ways, but Gefen et al. (2003). offer a distinction that is particularly useful here. They separate trust in the *competence* of the service provider the belief that it can do what it claims from trust in its *integrity* the belief that it will act in the customer's best interest rather than its own. In AI-enabled services, a third dimension has become increasingly salient: trust in the algorithm itself, which is distinct from trust in the organisation deploying it.

What changes in an Islamic banking context is that none of these three dimensions operates on purely secular ground. A customer evaluating a *Murabaha* contract is not simply asking "what will this cost me?” they are also, whether consciously or not, asking "is this arrangement one I can enter in good conscience?". A customer evaluating whether to engage with an AI advisory tool is not only asking "will this tool give me accurate information?" and "does the bank have my interests at heart?" but also "is this tool producing guidance that is consistent with Islamic principles?" Raza et al. (2019) found in their study of mobile banking adoption across Islamic banks that Sharia compliance perceptions were among the strongest predictors of acceptance stronger in many specifications than perceived usefulness or ease of use. That finding is consistent with the broader evidence from Morgan and Hunt (1994) that trust is foundational to the maintenance of ongoing service relationships, not merely a precondition for initial adoption.

The significance of trust for our purposes is that it shapes not just whether customers use AI tools but how they use them. A customer who trusts the religious integrity and technical reliability of an AI advisory system is likely to engage actively with the explanations it provides reading them carefully, asking follow-up questions, and applying the information to real financial decisions. A customer with low trust is more likely to use the tool instrumentally, completing a transaction with minimal engagement. The *quality* of the AI interaction, in other words, depends on trust in a way that the adoption decision may not. This distinction is what motivates us to treat trust as a moderator of educational outcomes rather than simply as an antecedent of usage behaviour.

Theoretical Framework

Our analytical framework combines two established models of technology acceptance and extends them in a specific direction suited to the Islamic banking context.

The Technology Acceptance Model (Davis, 1989) proposes that an individual's decision to use a technology is shaped primarily by two perceptions: whether the technology will improve their performance (perceived usefulness) and whether using it will require significant effort (perceived ease of use). These constructs have been replicated across hundreds of studies and remain among the most consistently supported in the information systems literature.

The Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003) broadens this foundation by incorporating social influence the degree to which important others expect the individual to use the technology and facilitating conditions the degree to which the individual believes that an organisational and technical infrastructure exists to support use. UTAUT provides a richer picture of the adoption context and is particularly relevant in organisational settings like banking where bank-level infrastructure conditions individual behaviour.

Our study extends both frameworks by repositioning trust from an antecedent of adoption to a moderator of educational quality. TAM and UTAUT account for trust insofar as it shapes whether a customer chooses to use a technology at all. What they do not address is what happens after that initial adoption decision: specifically, whether the customer engages with the educational content that AI tools can deliver or simply uses the tool to complete transactions efficiently. A customer may adopt an AI banking tool and yet derive no financial literacy benefit from it if they treat every AI interaction as a means to an end rather than an opportunity to learn. Our argument developed formally in the hypotheses below is that trust is the key variable that determines which of these modes of engagement predominates.

Hypothesis Development

AI Integration and Financial Literacy

The core hypothesis of this paper is that customers who perceive higher levels of AI integration in their bank's digital services will report higher financial literacy. The theoretical pathway runs through the features of AI tools that differentiate them from static information delivery: personalisation, interactivity, availability at the moment of decision, and adaptive explanation depth. When AI tools are perceived as extensively embedded in the bank's service environment, customers have more frequent and richer opportunities to receive explanations of product features, compare options, and ask follow-up questions in ways that support genuine understanding rather than passive compliance (Lusardi & Mitchell, 2014).

We treat AI integration as a supply-side, bank-level construct the customer's perception of how extensively AI capabilities are deployed across the bank's digital channels rather than a measure of the customer's own adoption decisions. This operationalisation ensures that the hypothesis captures the relationship between what the bank provides and what the customer learns, rather than simply reflecting individual differences in digital engagement.
Given the cross-sectional design, we acknowledge from the outset that this hypothesis is tested as an association. It is plausible that more financially literate customers evaluate AI integration more positively, or that a reinforcing relationship operates in both directions. The hypothesis below states the expected direction of the primary effect:
H1: *Perceived AI integration is positively associated with customer financial literacy among users of Jordanian Islamic banks.*

Customer Trust as a Moderator
The second hypothesis follows directly from the theoretical argument in Section 2.4. If trust shapes how deeply customers engage with AI-generated content whether they read explanations, ask follow-up questions, and apply information to financial decisions then we should expect the association between AI integration and financial literacy to be stronger when trust is high than when trust is low.

Importantly, we do not claim that trust is a prerequisite for any positive association to emerge. Even customers with moderate trust may derive some educational benefit from AI interactions. Our hypothesis is that the *strength* of the association varies with trust: among high-trust customers, each unit increase in perceived AI integration should correspond to a larger increase in financial literacy than among low-trust customers.
H2: *Customer trust in AI-enabled banking services positively moderates the relationship between perceived AI integration and financial literacy, such that the positive association is stronger when customer trust is high.*

Methodology
Design and Analytical Approach
This is a quantitative, cross-sectional study. We collected survey data from Islamic bank customers at a single point in time and used PLS-SEM to estimate the associations between latent constructs and to test the moderation hypothesis. The choice of PLS-SEM over covariance-based SEM reflects three characteristics of the study: its prediction and exploration orientation rather than confirmatory model testing, the non-normal distribution of several indicators, and the relatively small number of observations relative to the complexity of the hypothesised model (Hair et al., 2021). Our primary goal in the structural model is to explain variance in financial literacy, which is well served by PLS-SEM's variance-maximisation criterion.

The cross-sectional design is the study's most important limitation with respect to inference. We cannot establish from these data whether AI integration produces financial literacy gains, whether financially literate customers seek out AI-rich banking environments, or whether some unmeasured third variable drives both. We address this limitation by framing all results as associations and by discussing alternative explanations wherever they are substantively important.

Setting and Target Population

The study was conducted within Jordan's Islamic banking sector, which at the time of data collection comprised three licensed full-service Islamic banks: Jordan Islamic Bank, Safwa Islamic Bank, and Jordan Dubai Islamic Bank. These three institutions collectively serve the large majority of customers who choose Islamic banking in Jordan and operate across multiple branches in Amman, Zarqa, Irbid, and smaller cities. Our target population was adults aged 18 and over who hold an account at one of these institutions and who had actively used at least one AI-enabled digital service a mobile banking application, an online banking portal with intelligent features, or an AI-powered chatbot at least once during the three months preceding data collection.

The three-month recency criterion is important for the validity of the study's measures. Perceptions of AI integration and trust in AI tools are unlikely to be stable or meaningful among customers who have not recently interacted with those tools. Applying this criterion ensures that respondents are evaluating a service environment they have direct and recent experience with, rather than forming impressions based on advertising or hearsay.

Sampling Procedure

Obtaining a sampling frame from the banks themselves was not possible. Jordanian banks like banks in most jurisdictions do not share customer lists with external researchers, and no authoritative register of active digital banking users exists in the public domain. We therefore adopted a convenience sampling approach that combined two channels: self-administered paper questionnaires distributed at bank branches, and an electronic survey distributed through social media.

Branch-based channel. Paper questionnaires were distributed in the customer waiting areas of branch offices in Amman, Zarqa, and Irbid between September and November 2024. We approached branch managers at multiple branches of each of the three banks to request permission to conduct the survey on their premises. In all cases where permission was granted, a trained research assistant was present during distribution to explain the study's academic purpose, answer questions, and collect completed questionnaires at the end of each session. Participation was voluntary, anonymous, and uncompensated.

Electronic channel. An identical questionnaire was built using Google Forms and distributed through WhatsApp groups and Facebook pages associated with personal finance, Islamic banking, and customer communities in Jordan. Participants were invited to share the link with others who met the eligibility criteria, introducing a limited snowball element into the sampling process. The screening question that opened the survey asking whether the respondent had used their Islamic bank's digital services in the past three months served as an automated eligibility filter: those who answered negatively were redirected to a thank-you page and their responses were excluded from the data file before analysis.

A total of 347 responses were collected: 203 through the branch channel and 144 through the electronic channel. Data cleaning removed 35 cases 22 with more than 10 per cent missing values across the main scales, 8 that failed attention check items, and 5 identified as duplicate submissions through IP address and response pattern screening in the electronic data. Consistent with what is typically observed in mixed-mode survey research, the large majority of removals (32 of 35) originated from the electronic channel, where duplicate submissions and incomplete responses are more common than in face-to-face paper administration. The final usable sample comprised **312 observations**: 200 from the branch channel (64.1%) and 112 from the electronic channel (35.9%), representing an effective utilisation rate of 89.9 per cent.

Before combining the two sub-samples, we tested whether the two channels had recruited comparable respondents. Chi-square tests revealed no statistically significant differences between branch-based and electronic respondents on any of the demographic variables included in the survey: gender ($\chi^2(1) = 1.24$, $p = .265$), age group ($\chi^2(4) = 3.87$, $p = .424$), education level ($\chi^2(3) = 4.12$, $p = .249$), or digital banking experience ($\chi^2(2) = 2.63$, $p = .268$). These results support the appropriateness of combining the two sub-samples for the main analysis.

Table 1 presents the demographic profile of the final sample. The sample skews male (61.2%) and toward the 26–35 age group (38.1%), consistent with the demographic profile of active digital banking users in Jordan. Educational attainment is relatively high, with 68 per cent of respondents holding a bachelor's degree or postgraduate qualification. Jordan Islamic Bank accounts for half the sample (50.3%), reflecting its larger market share among the three participating institutions an imbalance acknowledged in Section 6.3.

Table 1
Demographic Characteristics of Respondents (N = 312)

Characteristic	Category	n	%
Gender	Male	191	61.2
	Female	121	38.8
Age	18–25	63	20.2
	26–35	119	38.1
	36–45	81	26.0
	46–55	37	11.9
	56 and above	12	3.8
Education	Secondary or below	36	11.5
	Diploma	64	20.5
	Bachelor's degree	155	49.7
	Postgraduate	57	18.3
Digital banking experience	Less than 1 year	42	13.5
	1–3 years	129	41.3
	More than 3 years	141	45.2
Primary bank	Jordan Islamic Bank	157	50.3
	Safwa Islamic Bank	94	30.1
	Jordan Dubai Islamic Bank	61	19.6
Data collection channel	Branch-based	200	64.1
	Electronic (Google Forms)	112	35.9

Measures

All constructs were measured using five-point Likert-type scales (1 = strongly disagree, 5 = strongly agree). Items were adapted from established instruments and then translated into Arabic following a forward-backward translation protocol with two independent bilingual translators. Discrepancies were resolved by discussion, and the Arabic version was pre-tested with 38 active digital banking customers before the main data collection. Based on pilot feedback, we simplified the wording of five items that participants found ambiguous; no items were dropped.

Perceived AI Integration (5 items) measures the customer's perception of how extensively AI-based functionalities are embedded in the bank's digital service environment. Items were adapted from Venkatesh et al. (2003) and Raza et al. (2019), modified to focus specifically on AI-based explanatory and advisory features. A sample item reads: *"My bank's mobile application uses intelligent tools to help me understand the features and terms of its financial products."* This construct captures a supply-side characteristic of the bank as experienced by the customer and is conceptually distinct from the customer's own adoption of specific AI features.

Financial Literacy (6 items) operationalises the construct as a self-report measure covering both general financial knowledge and Islamic finance–specific understanding, following Lusardi and Mitchell (2014) and Iqbal and Mirakhor (2011). A sample item reads: *"I am able to explain the difference between a Murabaha financing contract and a conventional bank loan."* We use self-reported rather than objective literacy assessment because the survey format and sample size make objective testing impractical; we acknowledge this as a limitation in Section 6.4.

Customer Trust (4 items) captures confidence in the technical reliability and Sharia compliance of AI-enabled banking services, drawing on Gefen et al. (2003) and Raza et al. (2019). A sample item: *"I trust that my bank's AI-based tools provide information that is consistent with Islamic principles."*

Digital Self-Efficacy (4 items control variable) measures individual confidence in using digital banking technologies without external assistance, adapted from Davis (1989). Including this control ensures that observed associations between AI integration and financial literacy are not simply artifacts of individual differences in digital competence.

A two-item **marker variable** measuring preference for branch-based over digital service delivery a construct with no theoretical connection to any of the study's main variables was embedded in the questionnaire. Near-zero, non-significant correlations between the marker and all focal constructs ($r \leq 0.09$, all $p > .05$) provide additional evidence that common method bias is not seriously distorting the results (Podsakoff et al., 2003).

Analytical Strategy

Analysis followed the two-stage PLS-SEM procedure recommended by Hair et al. (2021). In the first stage, the reflective measurement model was evaluated using four criteria: indicator reliability (outer loadings ≥ 0.70), internal consistency (Cronbach's alpha and composite reliability ≥ 0.70), convergent validity (AVE ≥ 0.50), and discriminant validity assessed through the HTMT ratio, with bootstrap confidence intervals computed for all pairwise values. In the second stage, the structural model was estimated through bootstrapping with 5,000 resamples, yielding path coefficients, t-statistics, and 95 per cent bias-corrected confidence intervals. Effect sizes (f^2) were interpreted using Cohen's (1988) benchmarks. Predictive relevance (Q^2) was assessed through blindfolding with an omission distance of seven; positive Q^2 values confirm that the model predicts the endogenous construct better than mean substitution (Stone, 1974; Geisser, 1975).

The moderating effect of customer trust was tested using the two-stage orthogonalisation procedure (Henseler & Chin, 2010), which prevents multicollinearity between the interaction term and its constituent predictors and yields stable estimates of the moderation coefficient. Digital self-efficacy was included as a control predictor throughout.

Common Method Variance
We took both procedural and statistical steps to assess common method variance risk (Podsakoff et al., 2003). Procedurally, predictor and outcome constructs were placed in separate questionnaire sections with neutral headings and transitional text, negatively worded items were included in three of the four scales, and the marker variable described above was embedded in the instrument. Statistically, Full Collinearity VIF diagnostics (Kock, 2015) returned values between 1.42 and 2.15 for all latent variables comfortably below the 3.3 threshold and marker variable correlations were uniformly small and non-significant. Taken together, these results indicate that common method bias is not a serious threat to the validity of our findings.

Results
Common Method Variance Screening
We began the analysis by testing whether common method variance might be inflating the relationships between constructs a concern that applies to any study where the same respondents provide all the data in a single sitting. Following Kock (2015), we computed Full Collinearity VIF values for all latent variables by regressing each construct on all the others. Values above 3.3 would have indicated potentially serious contamination; the values we obtained ranged from 1.42 to 2.15, all comfortably below that threshold (Table 2). The correlations between the embedded marker variable and the four focal constructs were uniformly small and non-significant ($r \leq 0.09$, all $p > .05$), providing supplementary reassurance that our results are not driven by method artefacts (Podsakoff et al., 2003).

Table 2
Full Collinearity VIF Diagnostics

Construct	Full Collinearity VIF
AI Integration	1.87
Financial Literacy	2.15
Customer Trust	1.74
Digital Self-Efficacy	1.42

Note. Values below 3.3 indicate acceptable levels of common method bias (Kock, 2015).

Measurement Model

Reliability and Convergent Validity

Table 3 summarises the outer loadings, Cronbach's alpha, composite reliability, and AVE for each of the four constructs. Starting with indicator reliability: all items loaded at or above 0.70 with two exceptions, both within the Financial Literacy scale. FL3 (*"I understand how profit rates are calculated in Islamic savings accounts"*) loaded at 0.68 and FL5 (*"I can explain the risk distribution in a Mudaraba contract"*) at 0.67. These two items address Islamic finance–specific knowledge dimensions that are conceptually important to the breadth of the financial literacy construct, and removing them would have narrowed its coverage in a way we judged theoretically unjustifiable. Hair et al. (2021) note that items approaching but falling marginally below the 0.70 guideline may be retained when theoretical breadth would otherwise be compromised, and we followed that guidance here.

Internal consistency was satisfactory across all constructs. Cronbach's alpha values ranged from 0.791 to 0.874, and composite reliability values ranged from 0.830 to 0.905, all exceeding the 0.70 minimum. AVE values fell between 0.580 and 0.721, all above the 0.50 threshold, confirming that each construct captures more variance in its indicators than measurement error does.

Table 3

Measurement Model Reliability and Convergent Validity

Construct	Items	Outer Loadings (Range)	Cronbach's α	Composite Reliability (ρ_a)	AVE
AI Integration	5	0.71–0.86	0.832	0.891	0.654
Financial Literacy	6	0.67–0.84	0.791	0.845	0.580
Customer Trust	4	0.82–0.91	0.874	0.905	0.721
Digital Self-Efficacy	4	0.72–0.88	0.801	0.830	0.648

Note: N = 312. Two Financial Literacy indicators retained below 0.70 loading threshold to preserve Islamic finance–specific construct breadth.

Discriminant Validity

We assessed discriminant validity using HTMT ratios rather than the Fornell-Larcker criterion (Fornell & Larcker, 1981), following the recommendation of Henseler et al. (2016) that HTMT provides a more sensitive and reliable test of construct distinctiveness. Table 4 shows pairwise HTMT values; all fall below the conservative 0.85 threshold. The highest value in the matrix is 0.76 between AI Integration and Customer Trust not unexpected given their theoretical proximity, but not high enough to raise serious concerns about construct overlap. To reinforce this conclusion, we computed bootstrap confidence intervals for this specific pair using 5,000 resamples; the resulting 95 per cent interval of [0.64, 0.81] falls entirely below 0.85, confirming that the two constructs are empirically distinct with a high degree of statistical confidence.

Table 4
Heterotrait-Monotrait (HTMT) Ratios

	AI Integration	Financial Literacy	Customer Trust	Digital Self-Efficacy
AI Integration				
Financial Literacy	0.61			
Customer Trust	0.76 [0.64, 0.81]	0.58		
Digital Self-Efficacy	0.52	0.47	0.49	

Note: Values below 0.85 confirm discriminant validity (Henseler et al., 2016). 95% bootstrap CI reported for highest HTMT pair.

Structural Model: Main Effects
With the measurement model confirmed as reliable and valid, we estimated the structural model through bootstrapping with 5,000 resamples. Digital self-efficacy was included as a control predictor in all specifications. Table 5 presents the results.

Hypothesis 1 was supported. The path from AI Integration to Financial Literacy was positive, statistically significant, and of medium magnitude ($\beta = 0.42$, $t = 5.82$, $p < .001$, 95% CI [0.28, 0.56], $f^2 = 0.18$). In practical terms, this means that customers who perceive their bank's digital services as more extensively AI-enabled report meaningfully higher financial literacy, even after controlling for individual differences in digital self-efficacy. The effect size of $f^2 = 0.18$ crosses Cohen's (1988) threshold for a medium effect, suggesting the association is substantively real rather than a statistical artefact of large sample size.

The control variable, digital self-efficacy, was also positively and significantly associated with financial literacy ($\beta = 0.19$, $t = 3.14$, $p = .002$, 95% CI [0.07, 0.31], $f^2 = 0.06$). Customers who are more confident in navigating digital tools tend to report higher financial literacy independent of how AI-rich their bank's services are. This finding has its own practical significance, which we discuss in Section 5. Together, the two predictors explained 38 per cent of the variance in financial literacy ($R^2 = 0.38$) a level of explanatory power that is substantial for a multidimensional outcome construct while also leaving clear room for other contributing factors.

Table 5
Structural Model: Main Effects

Path	β	t	p	95% CI	f²	Decision
AI Integration → Financial Literacy	0.42	5.82	< .001	[0.28, 0.56]	0.18	H1: **Supported**
Digital Self-Efficacy → Financial Literacy	0.19	3.14	.002	[0.07, 0.31]	0.06	

Note: β = standardised path coefficient. f^2 benchmarks: small = 0.02, medium = 0.15, large = 0.35 (Cohen, 1988). R^2 (Financial Literacy) = 0.38. Bootstrap resamples = 5,000.

Moderation Analysis

We tested the moderating role of Customer Trust using the two-stage orthogonalisation procedure (Henseler & Chin, 2010). In the first stage, latent variable scores for AI Integration and Customer Trust were computed from the measurement model, and an interaction term was derived as the product of these scores residualised from both constituent predictors. This procedure ensures mathematical independence between the interaction term and its components, preventing multicollinearity from distorting the main effect estimates. In the second stage, the orthogonalised interaction term was added to the structural model alongside the main effects of AI Integration, Customer Trust, and the Digital Self-Efficacy control.

The results, presented in Table 6, show clear support for Hypothesis 2. The interaction term (AI Integration × Customer Trust) was positive and statistically significant ($\beta = 0.14$, $t = 2.52$, $p = .012$, 95% CI [0.03, 0.25]). The effect size of $f^2 = 0.05$ falls within the small range by Cohen's (1988) classification, which is important to acknowledge: trust amplifies the association between AI integration and financial literacy, but does so modestly. The pattern is consistent with the theoretical expectation AI integration retains a meaningful positive association with financial literacy even at lower trust levels, with trust operating as an amplifier rather than as an on/off switch.

A note on the R^2 change is necessary here. The moderated model produced $R^2 = 0.43$, an increase of 0.05 over the main effects model. This increase reflects the joint addition of two terms to the model Customer Trust as a main effect ($f^2 = 0.08$) and the orthogonalised interaction term ($f^2 = 0.05$) not the moderating term alone. The increment attributable specifically to the moderation effect is therefore captured by $f^2 = 0.05$, while the direct effect of trust on financial literacy accounts for the larger portion of the explained variance gain.
The main effect of AI Integration remained significant in the moderated specification ($\beta = 0.40$, $t = 5.63$, $p < .001$), and Customer Trust showed a significant direct association with Financial Literacy ($\beta = 0.22$, $t = 3.47$, $p = .001$). The control variable retained significance ($\beta = 0.17$, $t = 2.89$, $p = .004$).

Table 6
Structural Model: Moderation Analysis

Path	**β**	**t**	**p**	**95% CI**	**f²**	**Decision**
AI Integration → Financial Literacy	0.40	5.63	< .001	[0.26, 0.54]	0.17	H1: **Supported**
Customer Trust → Financial Literacy	0.22	3.47	.001	[0.09, 0.35]	0.08	
AI Integration × Customer Trust → Financial Literacy	0.14	2.52	.012	[0.03, 0.25]	0.05	H2: **Supported**
Digital Self-Efficacy → Financial Literacy	0.17	2.89	.004	[0.06, 0.29]	0.05	

Note: Two-stage orthogonalisation used (Henseler & Chin, 2010). $R^2 = 0.43$. $\Delta R^2 = 0.05$ reflects addition of both Customer Trust main effect and interaction term. Bootstrap resamples = 5,000.

Predictive Relevance and Model Summary

Blindfolding with an omission distance of seven produced a Q^2 value of 0.24 for Financial Literacy. In the traditional PLS-SEM blindfolding framework, any positive Q^2 value indicates that the model predicts the endogenous construct better than a naïve benchmark of mean substitution a property known as predictive relevance (Stone, 1974; Geisser, 1975). The Q^2 of 0.24 confirms that this criterion is met. It is worth noting that Shmueli et al. (2019) propose benchmarks of 0.25, 0.50, and 0.75 for PLSpredict-based assessment, which is a distinct holdout-sample procedure from the blindfolding-based Q^2 reported here; applying those thresholds to our Q^2 would be methodologically inappropriate. Within the blindfolding framework, our result confirms predictive relevance, and the proximity of 0.24 to the lower Shmueli et al. threshold suggests the model's out-of-sample accuracy is modest a finding that underlines the need for additional predictors in future work.

Table 7
Summary of Model Fit and Predictive Indicators

Indicator	**Value**	**Benchmark**	**Interpretation**
R^2 Financial Literacy	0.43	> 0.26 substantial (Hair et al., 2021)	Substantial
ΔR^2 (moderation increment)	0.05	Consistent with $f^2 = 0.05$ for interaction	Small, meaningful
Q^2 Financial Literacy	0.24	$Q^2 > 0$ (Stone, 1974; Geisser, 1975)	Predictive relevance confirmed
Full Collinearity VIF (max)	2.15	< 3.3 (Kock, 2015)	No CMV concern
HTMT max (with 95% CI)	0.76 [0.64, 0.81]	< 0.85 (Henseler et al., 2016)	Discriminant validity confirmed

Table 8
Hypothesis Testing Summary

Hypothesis	**Statement**	**β**	**p**	**Decision**
H1	Perceived AI integration → Financial Literacy (+)	0.42	< .001	**Supported**
H2	Customer Trust moderates AI Integration → Financial Literacy (+)	0.14	.012	**Supported**

Discussion and Implications

What the Findings Actually Show

The headline finding is simple: customers at banks with more AI-integrated digital services report higher financial literacy. But the headline is the least interesting thing about these results, and before drawing practical conclusions it is worth pausing on what the data can and cannot tell us. The positive association between AI integration and financial literacy (H1) tells us that customers who perceive their bank's digital services as more extensively AI-enabled tend to report higher financial literacy not that deploying AI tools will automatically raise customers' financial literacy. The distinction matters. In a cross-sectional study, a positive association is consistent with several causal stories: AI tools help customers learn, more financially literate customers perceive AI more positively, or some third factor perhaps a bank's general commitment to customer education simultaneously raises both the quality of its digital services and the knowledge of its customers. We cannot adjudicate between these stories with the data at hand, and any interpretation of our findings should keep that in mind. What we can say with reasonable confidence is that the relationship between perceived AI integration and financial literacy is real, positive, and of medium magnitude not a statistical flicker attributable to chance, but also not so large as to suggest that AI tools are transforming financial literacy on their own. The effect size ($f^2 = 0.18$) and the unexplained variance in the outcome (57 per cent of the total, even in the moderated model) both point in the same direction: AI is one positive factor among several, and its educational contribution operates within a broader ecosystem that includes prior schooling, income, age, cultural attitudes toward finance, and the quality of human advisory relationships.

The significant control effect of digital self-efficacy ($\beta = 0.19$ in the main model) deserves more than passing mention. It tells us that customers who are more confident in their ability to use digital tools independently tend to report higher financial literacy, regardless of how AI-integrated their bank's services are. Two plausible interpretations run in opposite directions. One is that digitally confident customers extract more educational value from whatever AI features are available to them, suggesting that digital skills amplify AI's educational effect. The other is that digitally confident customers are simply more likely to seek out and engage with financial information in general, through multiple channels, making AI integration a relatively minor contributor to their overall knowledge. We cannot separate these interpretations here, but the implication for practice is the same in either case: banks and policymakers that focus exclusively on AI deployment without addressing the digital skills gap among less confident customers are likely to see the educational benefits of their investment concentrated among those who are already relatively advantaged.

The Efficiency–Comprehension Tension

It would be easy to read the positive H1 finding as a straightforward endorsement of AI investment for financial literacy purposes. We think that reading is too simple, and the medium rather than large effect size provides one reason to resist it.

Banks deploy AI tools for multiple purposes, and financial education is rarely their primary commercial objective. The most common business cases for AI in retail banking focus on cost reduction replacing human agents with chatbots, automating routine queries, and handling high transaction volumes with minimal staff. Tools designed around these objectives are typically calibrated to resolve customer interactions quickly and efficiently. Quick resolution and deep comprehension are not the same thing. A chatbot that answers a customer's question about their account balance in four exchanges has performed well by the metrics used to evaluate it; a chatbot that uses the same interaction to explain why the balance reflects a profit-sharing arrangement rather than an interest payment has achieved something educationally important but measurably slower and more expensive.

The implication is that the association between AI integration and financial literacy that we observe may be driven by the subset of banks, and the subset of AI tools within those banks, that have been designed with explanation in mind. Across the full distribution of AI integration levels in our sample, the average association is positive but it is almost certainly stronger among customers whose banks have invested in explanatory AI features than among those whose banks have invested primarily in efficiency. Our study cannot decompose this heterogeneity, but it points to a design question that deserves empirical attention: is the educational return on AI investment a function of deployment volume, or of deployment quality?

Trust, Sharia, and the Moderating Mechanism

The moderation finding (H2) adds an important qualifier to the main effect. The association between AI integration and financial literacy is significantly stronger when customers trust their bank's AI tools and that trust, in this context, is not simply trust in the technology's technical performance. The Customer Trust construct in this study explicitly captures Sharia-compliance trust alongside technical reliability trust, following the evidence from Raza et al. (2019) that religious perceptions are central, not peripheral, to how Islamic bank customers relate to digital services.

The theoretical mechanism we propose runs through engagement quality rather than adoption quantity. A customer with high Sharia-compliance trust is likely to read an AI-generated product explanation with the same receptive attention they would give to advice from a trusted religious advisor or bank staff member. A customer who doubts whether the AI tool is operating within Islamic principles may read the same explanation with scepticism, cross-checking it against their own understanding rather than updating their knowledge in response to it. The result, aggregated across thousands of interactions, is a higher average educational return for high-trust customers than for low-trust customers, even when the AI tools themselves are identical.

This mechanism has a direct implication for the tension between algorithmic opacity and Islamic transparency requirements that we identified in Section 2. The prohibition of *gharar* in Islamic commercial law is not simply about the financial structure of contracts it extends to informational asymmetries that leave customers unable to evaluate what they are agreeing to. An AI system that generates recommendations through an opaque process may technically facilitate a Sharia-compliant transaction while producing precisely the kind of asymmetric information environment that Islamic jurisprudence is concerned about. Our results suggest that customers sense this tension: those who are less confident that their bank's AI tools are religiously legitimate extract less educational value from AI interactions, suggesting that Sharia-compliance trust is not a soft reputational factor but a functional condition of the tool's educational effectiveness.

Theoretical Contributions

Our study contributes to three areas of the literature. The first is the body of work on financial literacy development. By examining AI integration as a potential determinant of self-reported Islamic financial literacy and by finding a positive association of meaningful magnitude we extend the financial literacy literature into a domain it has largely ignored: the supply-side conditions created by financial institutions' technology investments. Most literacy research focuses on individual-level predictors (education, income, age) or programme-level interventions (financial education curricula, employer workshops). Our findings point to a structural feature of the banking service environment as an additional relevant factor.

The second contribution is to technology acceptance research in Islamic banking. By repositioning trust from an antecedent of adoption to a moderator of educational quality, we advance beyond the question of whether customers use AI tools to ask what they get out of using them. TAM and UTAUT explain adoption; our extended framework begins to explain learning. The Sharia-specific content of the trust construct and its significant moderating effect demonstrates that Islamic banking cannot be treated as a generic context for universal adoption models. The institutional and jurisprudential features of the setting shape the mechanisms through which technology produces outcomes.

The third contribution is methodological. The full CMV assessment package we implemented combining procedural questionnaire design controls, a marker variable, and Full Collinearity VIF diagnostics together with the two-stage orthogonalisation approach for moderation and the bootstrap CI for the highest HTMT pair, represents a level of rigour that is recommended in methodological guidance but rarely fully implemented in published survey research in this field. We hope the approach serves as a practical template for future studies.

Implications for Islamic Bank Management

Three practical messages emerge from these findings for the management of Islamic banks in Jordan.

First, design AI for explanation, not only for efficiency. The positive association between AI integration and financial literacy is most plausibly driven by AI features that explain product features, describe Sharia compliance rationales, and invite customer questions not by features designed primarily to accelerate transaction processing. Banks that evaluate AI investment solely through cost reduction and customer satisfaction metrics are likely systematically underestimating its educational value. Building financial literacy KPIs into the evaluation framework for AI tool performance measuring whether customers who use AI advisory features demonstrate higher knowledge scores over time would create the right incentive structure for product development teams.

Second, communicate AI governance as a trust-building strategy, not only a compliance obligation. The moderating role of Sharia-compliance trust implies that investment in AI infrastructure only fully pays off educationally when customers believe the tools are operating within Islamic principles. Publishing independent Sharia board reviews of AI content, offering in-app explanations of how AI recommendations are generated, and providing easy access to a human advisor for customers who want to verify AI outputs are not peripheral service quality enhancements. They are direct levers on the variable that conditions the educational return on AI investment.

Third, address digital skills gaps alongside AI deployment. The significant control effect of digital self-efficacy signals that AI-driven literacy improvements are likely to be unevenly distributed. Customers who are less confident with digital tools derive less benefit from AI integration, suggesting that educational returns are already flowing disproportionately to more digitally capable customers. This pattern warrants explicit attention from banks targeting customer segments with lower digital confidence particularly older customers, those in smaller cities, and those with less formal education through branch-based tutorials, simplified in-app onboarding, and community outreach programmes.

Implications for the Central Bank of Jordan

Our findings offer two messages for the Central Bank of Jordan's financial inclusion and literacy agenda. On the positive side, the association between AI integration and financial literacy provides empirical support for the framing of digital banking expansion as a financial literacy instrument, not only an access and efficiency instrument. The 2023–2028 National Financial Inclusion Strategy's emphasis on AI-enabled services is therefore justified on educational as well as operational grounds provided the trust conditions are met.

On the cautionary side, the modest predictive relevance of our model ($Q^2 = 0.24$) and the substantial unexplained variance in financial literacy (57%) suggest that digital service expansion is not a substitute for structured financial education. School curricula, employer financial wellness programmes, and bank-led community education initiatives continue to address dimensions of financial literacy that AI tools, however well-designed, are unlikely to reach. Policymakers should resist framing digital transformation and financial education as alternatives; the evidence suggests they are complements.

Limitations and Future Research

The Causal Direction Problem

No amount of methodological care fully resolves the problem at the heart of a cross-sectional study: we do not know which way the arrow of causation points. The association between AI integration and financial literacy is consistent with the story we tell that AI tools help customers learn but it is equally consistent with the opposite story.

Who Our Sample Represents

Our respondents are not a representative cross-section of all Islamic bank customers in Jordan. They are customers who visited a branch or were active enough on social media platforms related to personal finance to encounter our survey and who, by eligibility criteria, had used digital banking services within the past three months. This is a population that is already more digitally engaged than the average Islamic bank customer. The association between AI integration and financial literacy that we observe may be weaker or absent among customers who use their bank's services primarily through branches, who are less comfortable with smartphones, or who live outside Amman, Zarqa, and Irbid. Whether our findings generalise to those segments is genuinely unknown, and we would caution against any reading of our results that treats digital banking expansion as a universal financial literacy solution reaching all customer groups equally.

The Bank Representation Imbalance

Half our sample (50.3%, n = 157) comes from Jordan Islamic Bank, reflecting that institution's dominant market position among the three participating banks. If the three banks differ in meaningful ways in the quality and design of their AI tools, in their Sharia supervisory arrangements, in the financial literacy of their typical customer then the overall associations we report are more representative of Jordan Islamic Bank's operating environment than of the sector as a whole. Future studies should build bank-level representativeness into their sampling design from the outset, perhaps through stratified sampling with quotas set proportional to each bank's customer base, and should test whether the AI integration–financial literacy association varies systematically across institutions.

Self-Reported Financial Literacy

We measured financial literacy through self-reported items rather than through an objective knowledge test. This was a pragmatic choice: administering a validated objective test to 312 respondents in two different data collection settings, while keeping the overall questionnaire to a manageable length, was not feasible within the constraints of this project. Self-report literacy measures are widely used in the literature and have demonstrated predictive validity for financial behaviours (Lusardi & Mitchell, 2014), but they are vulnerable to overconfidence bias. In the Islamic banking context, this vulnerability has a specific shape: customers may rate their understanding of *Murabaha* or *Mudaraba* products as higher than a direct knowledge test would reveal, because religious trust in the institution is conflated with genuine product comprehension. Future research should supplement self-report measures with objective Islamic financial literacy assessments, and should test whether the self-report and objective measures converge in their associations with AI integration and trust.

Trust Measured as a Composite

Customer trust in this study was treated as a single composite construct combining technical reliability and Sharia compliance sub-dimensions. The four-item scale showed strong reliability and convergent validity, and treating it as unidimensional was defensible given the study's exploratory orientation. However, collapsing two potentially distinct trust dimensions into a single score prevents us from examining whether they moderate the AI integration–literacy relationship in the same way or differently. It is plausible that Sharia-compliance trust is a more powerful moderator of financial literacy specifically, while technical reliability trust is a stronger moderator of general usage satisfaction. Future research should develop and validate a multidimensional trust scale that cleanly separates these two dimensions, and test their differential moderating roles within the same model.

Directions for Future Research

Beyond the design improvements implied by the limitations above, our findings point to several directions that we think are worth pursuing in their own right. First, comparative studies across multiple Islamic banking markets the Gulf Cooperation Council countries, Malaysia, and Indonesia all present contexts with different regulatory frameworks, different AI investment levels, and different baseline financial literacy environments would test the generalisability of the trust moderation mechanism and identify the boundary conditions under which it operates. Second, qualitative research involving in-depth interviews with bank customers at different trust and literacy levels, and with the product teams responsible for AI tool design, would illuminate the mechanisms through which AI interactions produce educational outcomes and identify which specific design choices matter most. Third, the finding that digital self-efficacy independently predicts financial literacy calls for research that examines the digital skills–financial literacy nexus more directly, including the question of whether targeted digital literacy programmes produce downstream financial literacy gains.

Conclusion

This paper set out to examine whether and under what conditions the integration of AI tools into Islamic banking is associated with higher financial literacy among customers. The answer our data provide is a qualified yes. Among 312 active digital banking customers drawn from three Jordanian Islamic banks, customers who perceive their bank's digital services as more extensively AI-enabled report meaningfully higher financial literacy, with an effect size that is moderate rather than large and that cannot be attributed to common method bias or to the demographic characteristics we controlled for. Customer trust specifically, confidence that AI tools are both technically reliable and Sharia-compliant strengthens this association significantly, though its incremental contribution is small. And individual digital self-efficacy is an independent positive predictor, a finding that points to the uneven distribution of AI's educational benefits across the customer base.

We draw three conclusions from these findings. The first is that AI tools in Islamic banking have real not merely hypothetical potential to contribute to customer financial literacy, but that potential is not self-executing. It depends on how AI tools are designed, on whether customers trust them, and on whether customers are equipped to engage with them productively. The second is that Sharia-compliance trust is a functional condition of AI's educational effectiveness in this context, not a soft reputational attribute. Investing in the appearance of Islamic legitimacy while deploying AI systems that customers actually distrust on religious grounds is likely to produce efficiency gains without the educational returns that would justify AI investment on financial inclusion grounds. The third is that the cross-sectional nature of our evidence imposes real humility on all of these conclusions: the associations we report are consistent with AI integration improving financial literacy, but they are also consistent with other causal stories. Testing those stories rigorously will require longitudinal and experimental designs that this study was not structured to provide.

What we can offer with reasonable confidence is a starting point: empirical evidence, from a context where such evidence was previously absent, that the relationship between AI banking services and customer financial literacy is real, positive, and shaped in theoretically meaningful ways by the degree of Sharia-informed trust that customers place in those tools.

References

Beck, T., Demirgüç-Kunt, A., & Merrouche, O. (2013). Islamic vs. conventional banking: Business model, efficiency and stability. *Journal of Banking & Finance*, *37*(2), 433–447. https://doi.org/10.1016/j.jbankfin.2012.09.016

Belanche, D., Casaló, L. V., & Flavián, C. (2019). Artificial intelligence in FinTech: Understanding robo-advisors adoption among customers. *Industrial Management & Data Systems*, *119*(7), 1411–1430. https://doi.org/10.1108/IMDS-08-2018-0368

Central Bank of Jordan. (2023). *National financial inclusion strategy 2023–2028*. Central Bank of Jordan. https://www.afi-global.org/wp-content/uploads/2024/04/National-Financial-Inclusion-Strategy-2023-2028.pdf

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

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319–340. https://doi.org/10.2307/249008

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39–50. https://doi.org/10.1177/002224378101800104

Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in online shopping: An integrated model. *MIS Quarterly*, *27*(1), 51–90. https://doi.org/10.2307/30036519

Geisser, S. (1975). The predictive sample reuse method with applications. *Journal of the American Statistical Association*, *70*(350), 320–328. https://doi.org/10.1080/01621459.1975.10479865

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2021). *A primer on partial least squares structural equation modeling (PLS-SEM)* (3rd ed.). Sage Publications.

Hassan, M. K., & Aliyu, S. (2018). A contemporary survey of Islamic banking literature. *Journal of Financial Stability*, *34*, 12–43. https://doi.org/10.1016/j.jfs.2017.11.006

Henseler, J., & Chin, W. W. (2010). A comparison of approaches for the analysis of interaction effects between latent variables using partial least squares path modeling. *Structural Equation Modeling: A Multidisciplinary Journal*, *17*(1), 82–109. https://doi.org/10.1080/10705510903439003

Henseler, J., Hubona, G., & Ray, P. A. (2016). Using PLS path modeling in new technology research: Updated guidelines. *Industrial Management & Data Systems*, *116*(1), 2–20. https://doi.org/10.1108/IMDS-09-2015-0382

Iqbal, M., & Molyneux, P. (2005). *Thirty years of Islamic banking: History, performance and prospects*. Edinburgh University Press.

Iqbal, Z., & Mirakhor, A. (2011). *An introduction to Islamic finance: Theory and practice* (2nd ed.). John Wiley & Sons.

Jagtiani, J., & Lemieux, C. (2019). The roles of alternative data and machine learning in fintech lending: Evidence from the LendingClub consumer platform. *Financial Management*, *48*(4), 1009–1029. https://doi.org/10.1111/fima.12295

Klapper, L., Lusardi, A., & van Oudheusden, P. (2015). *Financial literacy around the world: Insights from the Standard & Poor's ratings services global financial literacy survey*. Standard & Poor's. https://gflec.org/initiatives/sp-global-finlit-survey/

Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. *International Journal of e-Collaboration*, *11*(4), 1–10. https://doi.org/10.4018/ijec.2015100101

Lusardi, A., & Mitchell, O. S. (2014). The economic importance of financial literacy: Theory and evidence. *Journal of Economic Literature*, *52*(1), 5–44. https://doi.org/10.1257/jel.52.1.5

Morgan, R. M., & Hunt, S. D. (1994). The commitment–trust theory of relationship marketing. *Journal of Marketing*, *58*(3), 20–38. https://doi.org/10.1177/002224299405800302

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, *88*(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879

Rabbani, M. R., Khan, S., & Thalassinos, E. I. (2020). FinTech, blockchain and Islamic finance: An extensive literature review. *International Journal of Economics and Business Administration*, *8*(2), 65–86. https://doi.org/10.35808/ijeba/444

Raza, S. A., Shah, N., & Ali, M. (2019). Acceptance of mobile banking in Islamic banks: Evidence from modified UTAUT model. *Journal of Islamic Marketing*, *10*(1), 357–376. https://doi.org/10.1108/JIMA-04-2017-0038

Ringle, C. M., Wende, S., & Becker, J.-M. (2022). *SmartPLS 4*. SmartPLS GmbH. https://www.smartpls.com

Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J.-H., Ting, H., Vaithilingam, S., & Ringle, C. M. (2019). Predictive model assessment in PLS-SEM: Guidelines for using PLSpredict.

European Journal of Marketing, *53*(11), 2322–2347. https://doi.org/10.1108/EJM-02-2019-0189

Stone, M. (1974). Cross-validatory choice and assessment of statistical predictions. *Journal of the Royal Statistical Society: Series B (Methodological)*, *36*(2), 111–133. https://doi.org/10.1111/j.2517-6161.1974.tb00994.x

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, *27*(3), 425–478. https://doi.org/10.2307/30036540

World Bank. (2022). *Global Findex Database 2021: Measuring financial inclusion and the fintech revolution*. World Bank. https://doi.org/10.1596/978-1-4648-1897-4

Zouari, G., & Abdelhedi, M. (2021). Customer satisfaction in the digital era: Evidence from Islamic banking. *Journal of Innovation & Knowledge*, *6*(2), 121–131. https://doi.org/10.1016/j.jik.2020.11.004