# Human Resource Readiness and Perceived Risks in Generative AI Adoption: A Comparative Analysis of Islamic Digital Banking in Indonesia and Malaysia

Salamiah Muhd Kulal[1*], Dorris Yadewani[2], Muhammad Hendra[3], Donna Ikranova Febrina[4]

[1]*IOTA University College, Malaysia*
[2]*Universitas Ekasakti Padang, Indonesia*
[3]*Universitas Sumatera Barat, Indonesia*
[4]*Sekolah Tinggi Ilmu Administrasi LPPN, Padang, Sumatera Barat*

ABSTRACT
*This study examines readiness for, and perceived risks associated with, generative artificial intelligence (GenAI) adoption in Islamic digital banking institutions in Indonesia and Malaysia. Grounded in the Technology Acceptance Model and Perceived Risk Theory, the study employs a quantitative cross-sectional design with 287 banking professionals and digital banking customers selected through purposive sampling. Data were collected through a structured questionnaire and analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM). The findings show that generative AI readiness exerts a significant positive influence on adoption intention (β = 0.423, p < 0.001), while Shariah compliance risk (β = -0.281), data privacy risk (β = -0.196), and operational risk (β = -0.163) each impose significant negative effects. Multi-group analysis indicates that Shariah compliance risk weighs more heavily on adoption intention in Indonesia than in Malaysia, a pattern potentially associated with differences in Shariah governance infrastructure and regulatory context between the two jurisdictions. The study contributes empirical evidence on GenAI adoption within the institutional constraints distinctive to Islamic finance and offers practical implications for regulators, Shariah boards, and banking practitioners navigating AI-driven digital transformation.*

ABSTRAK
*Penelitian ini mengkaji kesiapan dan risiko yang dipersepsikan terkait adopsi kecerdasan buatan generatif (GenAI) di lembaga perbankan digital syariah di Indonesia dan Malaysia. Berlandaskan pada Model Penerimaan Teknologi dan Teori Risiko yang Dipersepsikan, penelitian ini menggunakan desain kuantitatif cross-sectional dengan 287 profesional perbankan dan nasabah perbankan digital yang dipilih melalui purposive sampling. Data dikumpulkan melalui kuesioner terstruktur dan dianalisis menggunakan Partial Least Squares Structural Equation Modelling (PLS-SEM). Temuan menunjukkan bahwa kesiapan AI generatif memberikan pengaruh positif yang signifikan terhadap niat adopsi (β = 0,423, p < 0,001), sementara risiko kepatuhan Syariah (β = -0,281), risiko privasi data (β = -0,196), dan risiko operasional (β = -0,163) memberikan efek negatif yang signifikan. Analisis multi-grup menunjukkan bahwa risiko kepatuhan Syariah lebih menonjol di Indonesia*

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*dibandingkan di Malaysia, mencerminkan perbedaan tingkat kematangan regulasi. Studi ini memberikan bukti empiris mengenai adopsi GenAI di tengah keterbatasan kelembagaan yang khas pada keuangan Islam, serta menawarkan implikasi praktis bagi regulator, dewan Syariah, dan praktisi perbankan yang menavigasi transformasi digital berbasis AI.*

*Keyword : Digital banking, Generative artificial intelligence, Islamic finance, Perceived risk, Technology adoption*



***Corresponding Author**
Author can be contacted through e-mail: Drzoeysally1@gmail.com

## 1. INTRODUCTION

When a Shariah-compliant bank in Jakarta or Kuala Lumpur lets a generative AI system draft a customer's financing recommendation, it inherits a problem no risk manual anticipated: the system can produce a fluent, confident answer that is subtly incompatible with Shariah principles, and neither the customer nor, often, the frontline officer would know to question it. This is the paradox now facing Islamic digital banking. Generative artificial intelligence (GenAI), including large language models such as GPT-4 and Gemini, promises exactly the efficiency gains that Islamic banks need in order to compete digitally: it can generate contextually coherent text, synthesise complex financial data, and automate advisory functions that previously required human expertise (Dwivedi et al., 2023). Yet the same generative fluency that produces this efficiency also makes GenAI's outputs difficult to audit against the one standard on which an Islamic bank's legitimacy ultimately rests, namely Shariah compliance. In conventional banking, GenAI applications span customer service automation, fraud detection, personalised financial planning, compliance monitoring, and credit risk assessment; in Islamic banking, each of these functions carries an additional, unfamiliar layer of risk. Empirical evidence on how regulated financial institutions actually navigate this tension nonetheless remains thin. Moharrak and Mogaji (2025), drawing on interviews with bank managers, found that much of the existing literature on GenAI in banking is speculative rather than grounded in organisational data, and that managerial preparedness for the technology has been particularly underexplored. Recent experimental work by Jokhio and Jaffer (2024), which tested general-purpose large language models directly against Shariah advisory scenarios, reinforces this concern: the models could flag some compliance issues but struggled to cite Shariah references reliably or to propose actionable remedies, which suggests the risk in question is already observable rather than purely hypothetical. This gap is more acute still for Islamic banking institutions, whose deployment of GenAI introduces a layer of institutional complexity that has received insufficient scholarly

attention.

Islamic banking operates under Shariah principles that mandate ethical conduct, prohibit interest (riba), and require transparency in financial transactions. The sector's growth across Southeast Asia has been substantial: Bank Negara Malaysia reported total Islamic banking assets exceeding RM 1.14 trillion in 2023, representing 40.3 percent of total banking system assets (Bank Negara Malaysia, 2023). In Indonesia, the Otoritas Jasa Keuangan (OJK) reported aggregate Islamic banking assets of IDR 861.22 trillion as of December 2023, with the sector continuing on a double-digit growth trajectory (OJK, 2024). The strategic deployment of GenAI within these institutions is therefore not merely a technological question but a governance, jurisprudential, and risk management challenge, one whose stakes rise in direct proportion to the sector's growth.

Whether banks and their customers actually embrace GenAI, however, depends less on what the technology can technically do than on what they perceive it might get wrong. Perceived Risk Theory (Bauer, 1960; Featherman & Pavlou, 2003) has long shown that adoption intentions are shaped as much by anticipated risk as by anticipated benefit, and GenAI sharpens this dynamic because its errors are harder to anticipate than those of earlier banking technologies: a GenAI system can fail fluently, producing an answer that reads as authoritative while being wrong in ways a user has no easy way to detect. Three risk perceptions are especially salient in this setting. Shariah compliance risk concerns the possibility that GenAI-generated advice, documentation, or product recommendations may inadvertently violate Shariah principles, a risk with no direct equivalent in conventional banking and one that threatens the institution's core religious legitimacy rather than merely its operational reliability. Data privacy risk reflects concern that GenAI systems, which process and are often trained on large volumes of sensitive financial data, may expose or misuse customer information. Operational risk captures the more familiar worry that GenAI outputs may be unreliable, prone to hallucination, or delegated too much decision authority without adequate human oversight.

This study treats banking professionals and retail customers as two distinct informant groups rather than as interchangeable respondents, and it is useful to state that scope condition before describing the sample. Professionals working in the digital banking, IT, or compliance units of an Islamic bank bring institutional knowledge of how GenAI is deployed and governed internally, so their responses speak most directly to organisational readiness and to Shariah compliance risk as a governance concern. Customers who actively use Islamic digital banking applications bring an experiential perspective on GenAI-mediated services, such as chat-based advisory tools or automated product recommendations, so their responses speak more directly to

adoption intention as a use decision. The research model is specified at the level of individual perception for both groups, consistent with TAM's original formulation as an individual-level model (Davis, 1989), while recognising that professionals and customers may weight the same risk differently because of their differing exposure to Shariah governance mechanisms. This dual-informant design is treated here as an explicit scope condition of the study, and its consequences for interpreting the pooled path estimates are revisited in the limitations section.

Despite a growing body of literature on AI adoption in financial services (Lee & Shin, 2018; Huang & Rust, 2021) and on digital banking adoption in emerging markets (Alalwan et al., 2017; Marakarkandy et al., 2017), three adjacent streams still leave Shariah compliance risk under-specified. The AI adoption literature treats risk mainly as privacy risk or performance risk, with no construct for religious-legitimacy risk (Bag, 2025). The Islamic fintech governance literature, including Kismawadi (2025) and Arsyad et al. (2026), discusses Shariah compliance mainly as a supervisory and legal design problem, addressed through governance frameworks rather than measured as a perception that varies across individuals and predicts behavioural intention. The Islamic banking technology-adoption literature, in turn, has predominantly applied TAM or UTAUT frameworks to conventional digital banking (Venkatesh et al., 2012; Boonsiritomachai & Pitchayadejanant, 2019) without treating Shariah compliance as a distinct risk construct that moderates, rather than simply co-occurs with, technology adoption decisions. What this study adds is not the observation that Shariah compliance matters, which the governance literature has already established, but the operationalisation of Shariah compliance risk as a perceptual, individual-level construct that can be measured, validated, and tested as a negative predictor of adoption intention, and whose inhibitory strength can be directly compared against data privacy risk and operational risk within the same model. The comparative institutional context adds further interest: Malaysia operates a more mature and codified Islamic fintech regulatory framework (Bank Negara Malaysia, 2024), whereas Indonesia's Islamic finance ecosystem remains in an earlier consolidation phase under the OJK Roadmap 2023-2027. This asymmetry offers a theoretically productive setting in which to test whether the same perceptual construct behaves differently across regulatory environments.

This study addresses this gap by investigating the determinants of GenAI adoption intention among banking professionals and customers in Indonesia and Malaysia, with specific attention to generative AI readiness, Shariah compliance risk, data privacy risk, and operational risk. Its contribution lies in conceptualising Shariah compliance risk as a theoretically grounded and empirically measurable construct within AI adoption research, distinct from the governance-only treatment it receives elsewhere in the literature, and in applying multi-group analysis to surface cross-country institutional differences. The findings carry implications for Islamic banking regulators, Shariah supervisory

boards, technology practitioners, and academics working at the intersection of AI governance, digital transformation, and Islamic finance.

## 2. THEORETICAL FRAMEWORK AND HYPOTHESES

### Technology Acceptance Model (TAM) and Generative AI Readiness

The Technology Acceptance Model, originally proposed by Davis (1989), holds that perceived usefulness and perceived ease of use are the primary determinants of behavioural intention to use a technology. The Unified Theory of Acceptance and Use of Technology (UTAUT), advanced by Venkatesh et al. (2003), extended this framework to incorporate social influence and facilitating conditions. In the context of GenAI, Dwivedi et al. (2023) argued that conventional TAM dimensions require augmentation to capture AI-specific characteristics such as generativity, hallucination risk, and algorithmic transparency. Building on this theoretical evolution, the present study operationalises generative AI readiness as a composite construct encompassing perceived usefulness, organisational infrastructure readiness, AI literacy, and willingness to integrate AI outputs into banking workflows. This construct aligns with the individual-level technology preparedness theorised by Parasuraman (2000) in the Technology Readiness Index.

Recent empirical work reinforces this reasoning and extends it to banking settings comparable to those examined here. Using the technology-organisation-environment framework, Kumar et al. (2025) surveyed banking employees in India and found that organisational readiness and perceived implementation barriers jointly shaped AI adoption intention, indicating that readiness in banking is as much an organisational property as an individual one. Working in an Indonesian banking context closely aligned with the geography of the present study, Ikhsan et al. (2025) extended TAM to AI adoption and found that perceived trust moderates the extent to which usefulness beliefs translate into continued use, a finding that anticipates the moderating logic tested later in this study. Taken together, these studies suggest that readiness is best understood as a multi-level construct that operates through both individual competence and organisational support structures, rather than through individual attitudes alone.

Two clarifications are needed before GAIR is used as a single predictor. First, TAM's original constructs, perceived usefulness and perceived ease of use, describe an individual's evaluation of a specific system already in front of them (Davis, 1989). GAIR is deliberately broader: it captures whether a person and their organisation are prepared for a class of technology whose exact capabilities are still unfolding, which is why this study follows Dwivedi et al. (2023) in treating GenAI-specific readiness as an extension of, rather than a direct substitute for, TAM's usefulness construct. Second, bundling perceived usefulness, organisational infrastructure readiness, AI literacy, and willingness to integrate AI outputs into a single GAIR

construct is not a claim that these four indicators are conceptually interchangeable. It is a claim, following Parasuraman's (2000) Technology Readiness Index and reinforced by Kumar et al.'s (2025) finding that organisational and individual readiness move together in banking settings, that the four indicators covary strongly enough in this population to be modelled as reflective indicators of one underlying readiness disposition rather than as four separate predictors. This modelling choice is tested empirically rather than assumed: the measurement model results reported in Section 4 provide the loadings, composite reliability, and average variance extracted that justify treating GAIR as a single reflective construct, and the discriminant validity results confirm that GAIR remains empirically distinct from the outcome it predicts.

Within the Islamic banking context, AI readiness extends beyond technical capacity to include the perceived compatibility of AI-generated outputs with Shariah principles. Iqbal and Mirakhor (2011) established that Islamic financial institutions operate under dual governance structures, namely conventional risk management and Shariah supervisory oversight, and that any technological adoption must satisfy both simultaneously. Generative AI readiness in this study therefore incorporates this dual-governance dimension as a contextual moderator. Based on TAM and extended AI readiness theory, the following hypothesis is proposed:

**H1: Generative AI readiness has a significant positive influence on adoption intention of GenAI in Islamic digital banking.**

***Perceived Risk Theory and GenAI Adoption***

Perceived Risk Theory, first advanced by Bauer (1960) and later extended to digital contexts by Featherman and Pavlou (2003), proposes that adoption of new technologies is significantly inhibited by the risks users perceive in their use. In e-banking and mobile banking research, dimensions such as privacy risk, financial risk, and performance risk have consistently emerged as significant adoption barriers (Pikkarainen et al., 2004; Raza et al., 2020). A recent systematic review of 157 studies on AI in banking and financial operations found that empirical treatment of risk perception, as distinct from technical risk management, remains fragmented across the literature, particularly for generative applications, and called for more granular, construct-level risk modelling of the kind pursued here (Bag, 2025). Three risk dimensions are theoretically and empirically relevant to GenAI within Islamic banking.

Shariah compliance risk refers to the probability that GenAI outputs, including automated financial advice, customer communications, or compliance documentation, may inadvertently violate Shariah principles such as the prohibition of gharar (excessive uncertainty) or recommend products incompatible with halal finance

standards. Hassan and Aliyu (2018) identified compliance risk as a defining structural feature of Islamic banking with no direct equivalent in conventional banking. This concern has gained fresh urgency with the arrival of generative tools capable of producing financial advice and documentation at scale. Zafar and Ali (2025) proposed a dedicated Shariah governance standard for generative AI in Islamic financial institutions, arguing that dual oversight, pairing a Shariah Supervisory Board with an AI governance committee, is necessary to manage the jurisprudential risks these systems introduce.

Data privacy risk concerns the potential for GenAI systems to process, store, or expose sensitive customer financial data without adequate governance controls, a concern amplified by the large training datasets and real-time processing characteristic of large language models (Lund & Wang, 2023). A recent survey of the security and privacy implications of GenAI in workplace settings catalogued vulnerabilities specific to generative systems, including unintended data retention, model inversion, and weak provenance controls, and argued that these risks are especially acute in data-sensitive sectors such as banking (Diro et al., 2025). Operational risk encompasses concerns about system errors, model drift, hallucination, and the delegation of consequential financial decisions to algorithmic systems. Interviews with Saudi Arabian bank board members identified inadequate oversight structures and unresolved cybersecurity vulnerabilities as central obstacles to responsible AI and machine learning adoption in banking (Eskandarany, 2024), while Moharrak and Mogaji (2025) reported that managers in regulated banking environments more often cited regulatory compliance and data governance, rather than technical performance alone, as the binding constraint on GenAI deployment. Based on this theoretical grounding, the following hypotheses are proposed:

**H2: Shariah compliance risk has a significant negative influence on adoption intention of GenAI in Islamic digital banking.**
**H3: Data privacy risk has a significant negative influence on adoption intention of GenAI in Islamic digital banking.**
**H4: Operational risk has a significant negative influence on adoption intention of GenAI in Islamic digital banking.**
**H5: Generative AI readiness moderates the negative relationship between Shariah compliance risk and adoption intention, such that higher readiness attenuates the inhibitory effect of Shariah compliance risk.**

The conceptual framework positions GenAI adoption intention as the dependent variable, with generative AI readiness as the primary positive predictor and Shariah compliance risk, data privacy risk, and operational risk as negative predictors. The interaction term between GAIR and SCR addresses the moderating role of readiness in attenuating risk-related adoption barriers. This framework is consistent with augmented TAM applications in Islamic fintech (Arner et al.,

2015) and with risk-acceptance trade-off models in the digital banking adoption literature.

***Research Model***

Figure 1 sets out the research model tested in this study. It specifies generative AI readiness (GAIR) as the sole positive predictor of GenAI adoption intention (AINT), and Shariah compliance risk (SCR), data privacy risk (DPR), and operational risk (OPR) as negative predictors (H1-H4). The dashed path denotes the hypothesised moderating role of GAIR in attenuating the negative SCR-AINT relationship (H5), positioning readiness as both a direct driver of adoption and a buffer against the risk dimension most distinctive to Islamic banking. The path estimates shown in the figure are reported and discussed in full in Section 4.

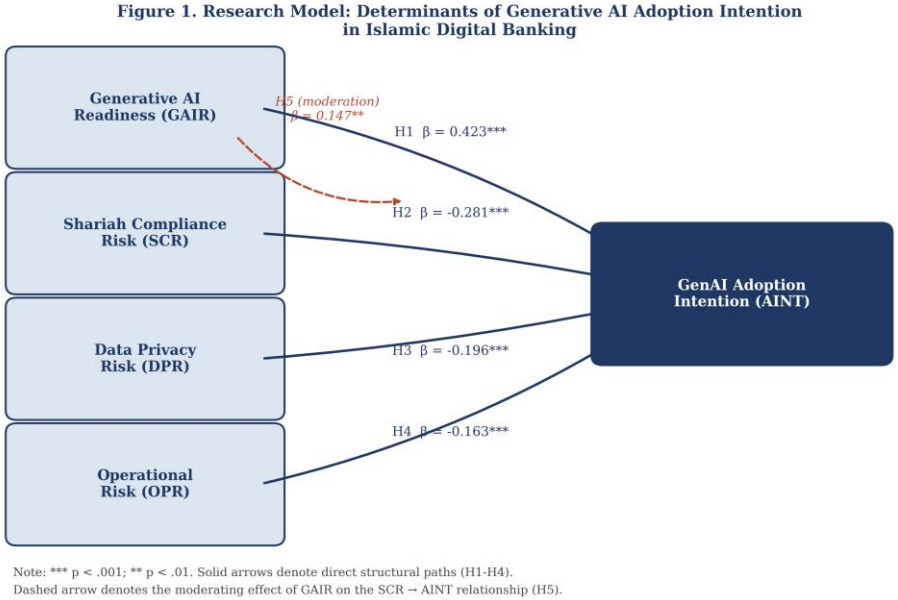



**Figure 1**
**Research Model: Determinants of Generative AI Adoption Intention in Islamic Digital Banking**

## 3. RESEARCH METHOD

### Research Design and Population

This study adopts a quantitative, cross-sectional survey design. The target population comprises banking professionals employed in Islamic banking divisions and retail digital banking customers actively using Islamic banking applications in Malaysia and Indonesia. The choice of quantitative methodology is justified by the study's objective to test theoretically derived hypotheses and to enable comparative statistical analysis across two national contexts, consistent with positivist epistemological assumptions (Creswell & Creswell, 2018).

### Sampling and Data Collection

Purposive sampling was employed to ensure that respondents possessed direct experience with, or institutional knowledge of, digital

banking services in Islamic financial institutions. In Malaysia, data were collected from professionals and customers affiliated with institutions under Bank Negara Malaysia's oversight, including Maybank Islamic, CIMB Islamic, and Bank Islam Malaysia Berhad. In Indonesia, respondents were drawn from institutions under the OJK's Islamic banking framework, including Bank Syariah Indonesia (BSI) and Bank Muamalat. A total of 320 questionnaires were distributed, of which 293 were returned and 287 were retained after removing incomplete or inconsistent responses, yielding a response rate of 89.7 percent. The final sample comprised 150 respondents from Malaysia and 137 from Indonesia.

Sample adequacy was assessed through the power-based approach that Hair et al. (2019) recommend in place of simpler rules of thumb, such as the widely used but comparatively crude '10-times rule.' Following Cohen's (1992) power tables for least squares regression, as reproduced by Hair et al. (2017), minimum sample size is a function of the number of predictor paths directed at the most complex construct in the model, the significance level, and the minimum R2 the researcher wishes to detect. The construct with the largest number of predictors in this study is adoption intention, which receives five paths (GAIR, SCR, DPR, OPR, and the GAIR x SCR interaction term). For a model of this complexity, a minimum of 45 respondents is required to detect an R2 of at least 0.25 at a 5 percent significance level with 80 percent statistical power (Hair et al., 2017). Because the structural model ultimately explained substantially more variance in adoption intention than this benchmark (R2 = 0.614; see Section 4), the achieved sample of 287 respondents comfortably exceeds the requirement and supports the reliability of the structural model estimates.

**Measurement Instrument**

The research instrument consisted of a five-point Likert scale questionnaire (1 = Strongly Disagree to 5 = Strongly Agree) with five latent constructs, each measured by three to four indicators adapted from validated scales. Generative AI Readiness (GAIR) was operationalised using four items adapted from Parasuraman (2000) and Davis (1989), modified to reflect GenAI characteristics. Shariah Compliance Risk (SCR) was measured using three items developed on the basis of Hassan and Aliyu (2018) and validated through expert review by two Shariah scholars with expertise in Islamic fintech governance. Data Privacy Risk (DPR) was measured using three items adapted from Featherman and Pavlou (2003). Operational Risk (OPR) was operationalised through three items drawing on the Basel III operational risk framework and adapted for AI contexts. Adoption Intention (AINT) was measured using four items adapted from Venkatesh et al. (2012). Table 1 lists the full item wording by construct, addressing the reviewer's request for a complete indicator inventory. The questionnaire was bilingual, offered in English and Bahasa Indonesia, with the Bahasa version independently back-translated to

verify semantic equivalence.

**Table 1.** Full List of Measurement Items by Construct

| Code | Item Wording | Adapted From |
|---|---|---|
| GAIR1 | I believe generative AI tools can genuinely improve how my bank (or the bank I use) serves customers. | Davis (1989) |
| GAIR2 | My organisation (or the bank I use) has the technical infrastructure needed to deploy generative AI responsibly. | Parasuraman (2000) |
| GAIR3 | I feel confident in my own understanding of what generative AI can and cannot reliably do. | Parasuraman (2000) |
| GAIR4 | I am willing to rely on outputs produced by generative AI in banking-related tasks or decisions. | Davis (1989); Dwivedi et al. (2023) |
| SCR1 | I am concerned that a generative AI system could produce advice or documentation that is not fully Shariah-compliant. | Hassan & Aliyu (2018) |
| SCR2 | I worry that a generative AI output could recommend a product or structure that resembles gharar or riba without this being obvious. | Zafar & Ali (2025) |
| SCR3 | I am unsure whether current oversight arrangements would catch a Shariah compliance error made by a generative AI system. | Zafar & Ali (2025); Iqbal & Mirakhor (2011) |
| DPR1 | I am concerned that a generative AI system could expose my (or my customers') financial data. | Featherman & Pavlou (2003) |
| DPR2 | I worry that data shared with a generative AI tool could be retained or reused without my knowledge. | Featherman & Pavlou (2003); Lund & Wang (2023) |
| DPR3 | I am concerned about how securely a generative AI system handles sensitive banking information. | Featherman & Pavlou (2003) |
| OPR1 | I am concerned that a generative AI system could produce an incorrect or misleading output (hallucination). | Basel III operational risk framework |
| OPR2 | I worry that too much decision authority could be delegated to a generative AI system without adequate human review. | Basel III operational risk framework |
| OPR3 | I am concerned about the reliability of a generative AI system during high-volume or time-sensitive banking operations. | Basel III operational risk framework |
| AINT1 | I intend to use (or support the use of) generative AI tools in Islamic banking services in the near future. | Venkatesh et al. (2012) |
| AINT2 | I would recommend the use of generative AI tools to colleagues or fellow customers. | Venkatesh et al. (2012) |
| AINT3 | I plan to continue using generative AI-enabled banking features where available. | Venkatesh et al. (2012) |
| AINT4 | Given the choice, I would prefer a generative AI-assisted service over a purely manual one, provided adequate safeguards are in place. | Venkatesh et al. (2012) |

*Note: The item wording represents the measurement instrument used in this study and was adapted from the cited validated sources.*

### Analytical Technique

Partial Least Squares Structural Equation Modelling (PLS-SEM) was performed using SmartPLS 4.0. PLS-SEM was selected given the study's predictive orientation, the complexity of the proposed

structural model, and its suitability for estimating the hypothesised relationships among the latent constructs (Hair et al., 2022). Because all constructs were measured through a single self-administered questionnaire completed by the same respondents, common method bias was assessed using the full-collinearity approach proposed by Kock (2015). Full-collinearity VIF values were examined for all latent constructs, with values below 3.30 indicating that common method bias was unlikely to represent a serious concern.

Following the four-step procedure for assessing reflective measurement models set out by Hair et al. (2022), the measurement model was evaluated for indicator reliability (outer loadings, with 0.708 as the minimum acceptable threshold), internal consistency reliability (Cronbach's alpha and composite reliability), convergent validity (average variance extracted, AVE > 0.50), and discriminant validity using the heterotrait-monotrait ratio (HTMT < 0.85). The structural model was assessed through path coefficients, t-statistics derived from 5,000 bootstrapping iterations, and R-squared values. Multi-group analysis (PLS-MGA) was used to examine cross-country differences between Malaysia and Indonesia.

## 4. DATA ANALYSIS & DISCUSSION

### Respondent Profile

Table 2 presents the demographic characteristics of the 287 respondents. The sample was predominantly male (56.8%), with the largest age cohort falling between 31 and 40 years (39.0%), reflecting the career stage most actively engaged with digital banking transformation initiatives. The majority held bachelor's degrees (50.2%) or postgraduate qualifications (49.8%), suggesting a respondent base with sufficient institutional knowledge to evaluate GenAI readiness and risk constructs meaningfully. Respondents with five to ten years of banking experience constituted the largest experience group (41.1%). Approximately 87.5% of respondents reported moderate to high familiarity with generative AI, consistent with the rapid diffusion of ChatGPT and related tools across professional contexts in the 2023-2025 period.

**Table 2.** Demographic Profile of Respondents (n = 287)

| Variable | Category | n (%) |
|---|---|---|
| **Country** | Malaysia | 150 (52.3%) |
| | Indonesia | 137 (47.7%) |
| **Gender** | Male | 163 (56.8%) |
| | Female | 124 (43.2%) |
| **Age** | 21-30 years | 88 (30.7%) |
| | 31-40 years | 112 (39.0%) |
| | 41-50 years | 71 (24.7%) |
| | > 50 years | 16 (5.6%) |

| | | |
|---|---|---|
| **Education** | Bachelor's Degree | 144 (50.2%) |
| | Master's Degree | 104 (36.2%) |
| | Doctoral Degree | 39 (13.6%) |
| **Banking Experience** | < 5 years | 79 (27.5%) |
| | 5-10 years | 118 (41.1%) |
| | > 10 years | 90 (31.4%) |
| **Familiarity with Generative AI** | High | 132 (46.0%) |
| | Moderate | 119 (41.5%) |
| | Low | 36 (12.5%) |

Source: Primary data (2025).

### Measurement Model Evaluation

The measurement model results presented in Table 3 confirm adequate reliability and validity for all constructs. Composite reliability values ranged from 0.868 (OPR) to 0.906 (AINT), all exceeding the threshold of 0.70 recommended by Hair et al. (2017). Cronbach's alpha values similarly satisfied the 0.70 criterion. AVE values ranged from 0.621 to 0.661, all surpassing the 0.50 convergent validity threshold. All indicator loadings exceeded the minimum acceptable value of 0.70, with the highest loading observed for AINT1 (0.821). These results confirm that the measurement model demonstrates satisfactory convergent validity.

**Table 3.** Measurement Model Results: Reliability and Convergent Validity

| Construct / Indicator | Loading | CR | AVE | Cronbach's Alpha |
|---|---|---|---|---|
| **Generative AI Readiness (GAIR)** | | 0.891 | 0.623 | 0.856 |
| GAIR1 | 0.774 | | | |
| GAIR2 | 0.812 | | | |
| GAIR3 | 0.798 | | | |
| GAIR4 | 0.781 | | | |
| **Shariah Compliance Risk (SCR)** | | 0.876 | 0.638 | 0.831 |
| SCR1 | 0.806 | | | |
| SCR2 | 0.791 | | | |
| SCR3 | 0.798 | | | |
| **Data Privacy Risk (DPR)** | | 0.883 | 0.654 | 0.842 |
| DPR1 | 0.815 | | | |
| DPR2 | 0.801 | | | |
| DPR3 | 0.813 | | | |
| **Operational Risk (OPR)** | | 0.868 | 0.621 | 0.820 |
| OPR1 | 0.779 | | | |
| OPR2 | 0.793 | | | |
| OPR3 | 0.801 | | | |
| **Adoption Intention (AINT)** | | 0.906 | 0.661 | 0.878 |
| AINT1 | 0.821 | | | |
| AINT2 | 0.809 | | | |

| | |
|---|---|
| AINT3 | 0.813 |
| AINT4 | 0.803 |

Note: CR = Composite Reliability; AVE = Average Variance Extracted.
Source: SmartPLS 4.0 output (2025).

**Table 3a.** Full Collinearity VIF (Common Method Bias Assessment)

| Construct | Full Collinearity VIF |
|---|---|
| GAIR | **1.014** |
| SCR | **1.564** |
| DPR | **1.534** |
| OPR | **1.566** |
| AINT | **1.533** |

*Note: Threshold for common method bias concern is VIF ≥ 3.3 (Kock, 2015).*

Table 4 presents HTMT ratios for discriminant validity assessment. All HTMT values fell below the conservative threshold of 0.85, confirming that each construct is empirically distinct from the others. The highest HTMT ratio was observed between GAIR and AINT (0.712), which is theoretically expected given the directional relationship between these constructs but remains below the threshold.

**Table 4.** Discriminant Validity: Heterotrait-Monotrait (HTMT) Ratios

| Construct | GAIR | SCR | DPR | OPR | AINT |
|---|---|---|---|---|---|
| **GAIR** | | | | | |
| SCR | 0.512 | | | | |
| DPR | 0.498 | 0.541 | | | |
| OPR | 0.476 | 0.567 | 0.584 | | |
| AINT | 0.712 | 0.488 | 0.501 | 0.463 | |

Source: SmartPLS 4.0 output (2025).

## Structural Model and Hypothesis Testing

The structural model explained 61.4% of the variance in adoption intention (R2 = 0.614), indicating a substantial predictive capability. The model's Stone-Geisser Q2 predictive relevance value was 0.448, confirming adequate predictive accuracy. Table 5 presents the path coefficients, standard errors, t-values, and hypothesis decisions for all five hypotheses; the substantive interpretation of these results, and their comparison against prior literature, is taken up in Section 5.

**Table 5.** Structural Model: Path Coefficients and Hypothesis Testing Results

| H | Relationship | Beta (β) | Std Error | t-value | p-value | Decision |
|---|---|---|---|---|---|---|
| H1 | GAIR -> AINT | 0.423 | 0.051 | 8.294 | < 0.001 | Supported |
| H2 | SCR -> AINT | -0.281 | 0.048 | 5.854 | < 0.001 | Supported |
| H3 | DPR -> AINT | -0.196 | 0.044 | 4.455 | < 0.001 | Supported |
| H4 | OPR -> AINT | -0.163 | 0.042 | 3.881 | < 0.001 | Supported |
| H5 | GAIR x SCR -> AINT | 0.147 | 0.038 | 3.868 | 0.002 | Supported |

Source: SmartPLS 4.0 bootstrapping output (5,000 iterations, 2025).

### *Multi-Group Analysis: Malaysia versus Indonesia*

Table 6 presents the PLS-MGA results comparing path coefficients across Malaysia and Indonesia; the interpretation of these differences is taken up in Section 5.

**Table 6.** Multi-Group Analysis: Malaysia versus Indonesia

| Path | Malaysia (β) | Indonesia (β) | Diff. | Significance |
|---|---|---|---|---|
| GAIR -> AINT | 0.441 | 0.402 | 0.039 | p = 0.312 (ns) |
| SCR -> AINT | -0.231 | -0.334 | 0.103 | p = 0.041* |
| DPR -> AINT | -0.174 | -0.218 | 0.044 | p = 0.283 (ns) |
| OPR -> AINT | -0.149 | -0.178 | 0.029 | p = 0.441 (ns) |

*Note: * p < 0.05; ns = not significant. Source: SmartPLS 4.0 PLS-MGA output (2025).*

## 5. DISCUSSION

This section interprets the results reported in Section 4 against the theoretical framework and prior literature, and it deliberately does not restate path coefficients beyond what is needed to anchor the discussion

### *Generative AI Readiness and Adoption Intention (H1)*

H1 was supported, with GAIR showing the strongest positive path to AINT of any predictor in the model. In this setting, that magnitude is explicable because GAIR is not simply an attitude toward a familiar tool; it is a judgement about whether a person and their institution can absorb a technology whose outputs still require active checking before use. Where perceived usefulness alone might explain interest in a GenAI feature, it is the added dimensions of infrastructure readiness and AI literacy that explain willingness to actually adopt it in a regulated setting. This result is consistent with TAM-based digital banking adoption studies (Venkatesh et al., 2012; Alalwan et al., 2017), and its magnitude aligns with Huang and Rust's (2021) finding that higher AI literacy correlated positively with adoption intent among financial professionals.

### *The Three Risk Dimensions and Adoption Intention (H2-H4)*

H2, H3, and H4 were all supported, confirming that Shariah compliance risk, data privacy risk, and operational risk each significantly reduce adoption intention. The size of the Shariah compliance risk effect, larger than either data privacy risk or operational risk, is best explained by what a Shariah violation actually threatens. A data breach or a hallucinated output can be patched, apologised for, or corrected without touching a bank's core claim to legitimacy; a Shariah violation calls that legitimacy into question directly, because Shariah compliance is not one risk category among others for an Islamic bank but the basis on which the institution is

permitted to operate at all. This reading is consistent with Hassan and Aliyu (2018), who identified compliance governance as a central determinant of technology uptake in Islamic financial institutions, and it extends their argument into the domain of generative AI specifically. The ordering of the three risk paths, Shariah compliance risk ahead of data privacy risk ahead of operational risk, suggests that respondents in this sector do not treat GenAI primarily as a technology problem to be debugged, but as a legitimacy problem to be governed, a framing consistent with Iqbal and Mirakhor's (2011) account of Islamic banks as dual-governed institutions in which Shariah supervision, not conventional risk management alone, defines what counts as an acceptable technology.

### *The Moderating Role of Readiness (H5)*

H5 was supported: the interaction term GAIR x SCR positively predicts AINT, confirming the coping-resource mechanism proposed in Section 2. Figure 2 translates the reported coefficients into simple slopes at one standard deviation above and below mean readiness. The estimated effect of Shariah compliance risk on adoption intention falls from -0.428 among respondents with low readiness to -0.134 among those with high readiness. Readiness does not remove the concern; it changes how much that concern subtracts from adoption intention, which is consistent with the mechanism proposed earlier: readiness gives respondents the competence to evaluate and contain the risk rather than reason it away.

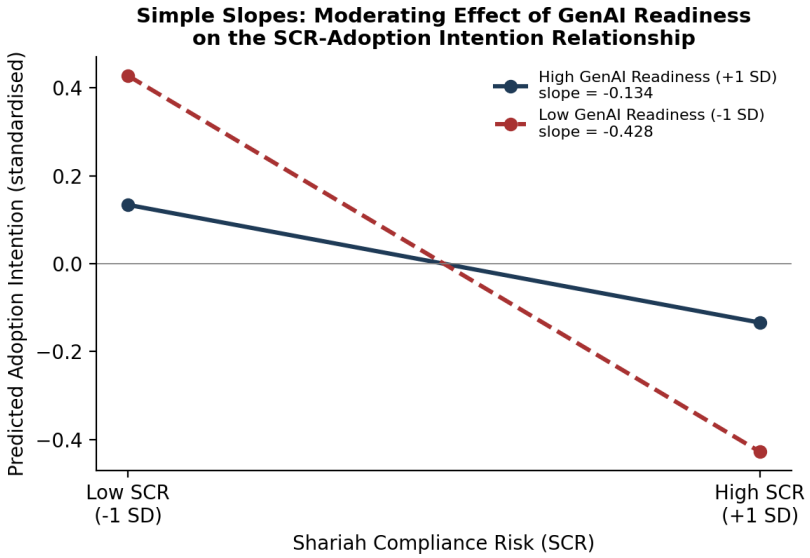



***Figure 2***

***Simple-Slope Plot for the GAIR x SCR Interaction (H5), Derived from the Reported Path Coefficients in Table 5***

*Note: Slopes computed following Dawson (2014); values are derived*

*arithmetically from the standardised coefficients already reported in Table 5 (b(SCR) = -0.281; b(GAIR×SCR) = 0.147) and are not independent new estimates.*

This has a direct implication for capacity-building programme design, developed further in the practical implications below: training should be built around verification skill, for example knowing what a given GenAI output should be checked against, rather than around reassurance that the technology is safe, since respondents evidently keep weighing Shariah risk even at high readiness.



***Cross-Country Differences (Multi-Group Analysis)***

The MGA results show that the GAIR-AINT, DPR-AINT, and OPR-AINT paths do not differ significantly between Malaysia and Indonesia, but the SCR-AINT path does, with Indonesian respondents showing a markedly stronger negative effect. A regulatory-maturity account, attributing this to Malaysia's more codified Islamic Financial Services Act 2013 and Value-Based Intermediation framework relative to Indonesia's still-developing OJK provisions, is a reasonable starting explanation but is unlikely to be complete on its own, since GAIR, DPR, and OPR showed no equivalent cross-country gap despite Indonesia and Malaysia also differing on general digital and data-protection regulation. A regulatory-maturity story alone would predict some spillover into those other paths too.

Two more specific mechanisms are worth considering. First, Malaysia's Shariah governance apparatus is anchored in a single national Shariah Advisory Council with binding authority under the Islamic Financial Services Act 2013, which gives banks and customers a common reference point for what counts as compliant, potentially lowering perceived compliance risk even before a specific AI application is evaluated. Indonesia's Shariah governance is more distributed across the National Sharia Board (DSN-MUI) and individual bank Shariah Supervisory Boards, which may leave more room for perceived ambiguity about how an AI-generated output would be judged. Second, digital fatwa and Shariah-technology interface infrastructure, of the kind Zafar and Ali (2025) argue is needed for GenAI specifically, appears further advanced in Malaysia's Value-Based Intermediation initiatives than in Indonesia's still-developing AI governance provisions, which would help explain why the cross-country gap concentrates in SCR rather than appearing across all three risk types. Testing these two mechanisms directly, rather than inferring them from a country-level proxy, is a natural next step for research in this area, and is noted again in Section 6.

### *Theoretical Implications*

The theoretical contribution translates into three specific directions for future model-building, rather than into a general claim that theory has been extended. First, researchers modelling AI adoption in religiously or ethically regulated sectors should test legitimacy risk as a construct distinct from privacy risk or performance risk, following the operationalisation used here, rather than folding it into a generic trust or risk variable; doing so allows its relative weight against other risks to be estimated rather than assumed. Second, readiness-risk interaction should be specified and tested as a coping-resource mechanism, not simply reported as a significant moderator: this means measuring, where feasible, the specific competence a respondent gains, such as the ability to identify what a given output should be checked against, rather than inferring the mechanism after the fact from a significant coefficient. Third, cross-national comparisons of Islamic finance technology adoption should include a measure of Shariah governance structure, for instance centralised versus distributed supervisory authority, as a candidate moderator or covariate, since the present findings suggest that regulatory maturity alone under-explains why only one of three risk paths differed between Malaysia and Indonesia.

### *Practical and Managerial Implications*

Three specific actions follow from the findings, rather than a general recommendation to invest in readiness. First, because GAIR represents the strongest individual predictor of adoption intention in the model, capacity-building efforts should place substantial emphasis on perceived usefulness, infrastructure readiness, AI literacy, and willingness to integrate AI outputs, while continuing to address the three identified risk dimensions, which the H5 result suggests will not remove the Shariah compliance risk effect regardless of budget. Second, because Shariah compliance risk remains significant even at high readiness, banks deploying GenAI in customer-facing or advisory functions should establish a documented Shariah-verification checkpoint for GenAI outputs before release, for example a standard operating procedure requiring a named reviewer to sign off against a specific Shariah reference before an AI-generated recommendation reaches a customer, consistent with the dual governance model proposed by Zafar and Ali (2025). Third, for banks operating in both Malaysia and Indonesia, the multi-group results indicate that a single regional AI governance template is unlikely to fit both markets equally; institutions should budget separately for a more detailed Shariah-verification protocol in the Indonesian operation until the DSN-MUI and OJK governance provisions for AI-specific applications are further

codified. For regulators, and OJK in particular, the finding that Shariah compliance risk is both the strongest inhibitor and the one most sensitive to institutional context supports prioritising AI-specific Shariah governance standards, of the kind already drafted by Zafar and Ali (2025), over generic AI risk guidance that does not name Shariah compliance as a distinct category.

## 6. CONCLUSION, LIMITATIONS, AND FUTURE RESEARCH

This study investigated the determinants of generative AI adoption intention in Islamic digital banking across Malaysia and Indonesia. Generative AI readiness was the strongest determinant of adoption intention, consistent with the view that adoption in this sector functions as an institutional capability judgement rather than a purely individual attitude. Among the three risk dimensions, Shariah compliance risk was the most inhibitory, because it threatens the religious legitimacy on which Islamic banking depends rather than merely its technical reliability. Readiness moderates, without eliminating, this effect, operating as a coping resource that helps respondents evaluate and manage Shariah compliance risk rather than a mechanism that reassures them it does not exist. Multi-group analysis showed that this risk operates more forcefully as an adoption barrier in Indonesia than in Malaysia, a difference this study attributes to divergent Shariah governance infrastructure rather than to regulatory maturity alone.

This study is subject to several limitations. The cross-sectional design limits causal inference, and longitudinal research tracking adoption behaviour after implementation would strengthen the findings. The purposive sampling approach restricts generalisation to the wider population of Islamic banking stakeholders. Pooling banking professionals and customers within a single structural model, while theoretically justified in Section 3, means the reported path coefficients represent an average across two groups whose institutional knowledge, exposure to Shariah governance mechanisms, and stake in the adoption decision differ; a professional's Shariah compliance risk perception is grounded in familiarity with internal controls, while a customer's is grounded in trust in the bank, and these may not carry equal weight even though the measurement model treats them as indicators of the same underlying risk perception. The measurement of Shariah compliance risk also relied on perceptual self-reporting, which may not fully capture the technical jurisprudential dimensions of the AI-Shariah interface.

Future research is encouraged to incorporate objective measures of Shariah compliance capability, extend the comparative framework to other ASEAN Islamic banking markets such as Brunei and Bangladesh,

disaggregate the professional and customer subgroups analytically once sample sizes allow rather than pooling them, test the centralised-versus-distributed Shariah governance mechanism proposed in Section 5 directly rather than inferring it from country membership, and examine the supply side through qualitative inquiry into how Shariah supervisory boards regard GenAI deployment within their own institutions.



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**APPENDICES**

Appendices consist of research instruments, supporting data, figures, and other material supporting the article and helping readers understand the research.