

Understanding Consumer Intention to Use Robo-Advisory Services: A Technology Readiness Perspective

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Abstract. Robo-advisory services are increasingly transforming the digital investment landscape by offering algorithm-driven financial advice. However, consumer adoption remains uneven, particularly in emerging markets where technological readiness and service awareness vary considerably. Drawing on the Technology Readiness Index (TRI), this study examines how individuals' technological predispositions—optimism, innovativeness, discomfort, and insecurity—influence their intention to use robo-advisory services, while integrating service awareness as a key cognitive mechanism. Using survey data from 180 Malaysian consumers, the study employs partial least squares structural equation modelling (PLS-SEM) to test the proposed framework. The results indicate that optimism and innovativeness exert significant positive effects on both awareness and adoption intention, while insecurity shows no significant direct influence on either outcome. Discomfort, however, demonstrates a more nuanced pattern: it negatively affects awareness but exerts a significant positive direct effect on adoption intention. Awareness emerges as the strongest predictor of adoption intention and serves as a key mediating mechanism, partially transmitting the effects of optimism and innovativeness. This study contributes to the FinTech literature by advancing a theoretically grounded framework that synthesises psychological predispositions and cognitive awareness to elucidate consumers' adoption intentions in AI-driven financial services. Practical implications are provided for FinTech providers seeking to accelerate adoption through awareness-building initiatives in emerging digital economies.

Keywords: robo-advisory services, artificial intelligence (AI), technology readiness index (TRI), awareness, intention, PLS-SEM

1. Introduction

The rapid expansion of financial technology (FinTech) has profoundly transformed the global financial services industry. Advances in artificial intelligence (AI), big data analytics, cloud computing, and automation provide unprecedented efficiency, scalability, and market accessibility, thereby challenging traditional intermediation models (Najem et al., 2025; Salem & Shahimi, 2025). Recent breakthroughs in AI-driven architecture further demonstrate how big-data-integrated decision-support mechanisms optimise asset allocation and operational execution (Yang, 2026). These technological developments have not only altered operational processes but have also redefined how financial advice, investment decision-making, and wealth management are conceptualised and delivered.

Within this evolving landscape, robo-advisory services have emerged as a pivotal innovation in wealth management. Defined as digital investment platforms that provide automated, algorithm-driven financial advice with minimal human intervention, robo-advisors leverage AI to offer standardised yet personalised solutions at scale (Kulkarni et al., 2025). By reducing advisory costs and lowering entry barriers for retail investors, these platforms broaden access to sophisticated portfolio management (Jung et al., 2018). This democratisation is facilitated by a structured and algorithm-driven operational model, in which digital client profiling and risk assessment mechanisms enable quantitative optimisation. As a result, these systems facilitate the construction of diversified investment portfolios that are continuously monitored and dynamically rebalanced in response to evolving market conditions (Tahvildari, 2025).

Notwithstanding their technological sophistication, the diffusion of robo-advisory services remains uneven across countries. Adoption has accelerated in developed economies, as reflected in rapid growth in assets under management (AUM), whereas uptake in emerging markets has been considerably more restrained (PW Consulting, 2025). Malaysia exemplifies this trend; despite proactive regulatory support via the Digital Investment Management (DIM) framework, consumer uptake remains in its infancy (ASNB Academy, 2025). Industry data indicate that AUM in Malaysia's robo-advisory segment increased only modestly from RM1.6 billion in late 2023 to RM1.9 billion by December 2024 (Fintech News Malaysia, 2025). This sluggish growth suggests that technological availability and regulatory scaffolding alone are insufficient to ensure mass-market success. Instead, the "bottleneck" appears to be rooted in the underlying psychological constructs that govern how consumers perceive AI-driven financial tools. To address this, the Technology Readiness Index (TRI) provides a robust framework for examining an individual's innate propensity to embrace new technologies, independent of specific system attributes (Parasuraman, 2000; Parasuraman & Colby, 2015).

The TRI conceptualises technology readiness through four distinct dimensions: optimism and innovativeness, which facilitate adoption, and discomfort and insecurity, which inhibit engagement. This dual-natured structure is particularly relevant to AI-driven investment services, where the perceived benefits of efficiency and cost reduction must coexist with consumer concerns over complexity, loss of control, and system trust.

Although prior studies, most notably Flavián et al. (2022), have established a framework integrating technology readiness and awareness in the context of robo-advisors, empirical evidence remains largely concentrated in developed Western markets. It remains unclear whether these psychological dynamics hold true in emerging economies like Malaysia, where different regulatory landscapes and lower market maturity may alter the interplay between readiness and awareness. Addressing these gaps, the present study examines how the dimensions of technology readiness, together with consumer awareness, influence Malaysian consumers' intentions to adopt robo-advisory services.

The study contributes to the FinTech literature in several ways. Primarily, it provides a contextual validation of the relationship between technology readiness and service awareness within an emerging market, offering a necessary comparison to findings from more mature digital economies. Additionally, it integrates psychological predispositions with cognitive awareness to provide a more holistic explanation of adoption intention in the high-stakes domain of automated investment. Finally, this study

offers evidence-based insights for practitioners and policymakers aiming to overcome the specific adoption bottlenecks prevalent in developing financial ecosystems.

2. Literature Review

Robo-advisory services have emerged as a significant innovation within the broader FinTech ecosystem, reflecting the increasing integration of AI and algorithmic decision-making in financial services. Robo-advisors are digital platforms that provide automated financial advice and portfolio management using algorithmic decision rules and data-driven models, typically requiring minimal or no human intervention (Cardillo & Chiappini, 2024). Recent research further elaborates that modern robo-advisors bring together advanced design requirements and user interface features to enhance investor adoption and interaction, while also leveraging investor profiling and behavioural analytics to tailor recommendations (Jung et al., 2018; Namyslo et al., 2025).

The diffusion of robo-advisory services has been driven by several factors, including increasing demand for low-cost investment products, declining confidence in traditional financial intermediaries following the global financial crisis, and advances in data analytics and computing power that enable scalable automation of financial advice (D'Acunto et al., 2019). From a policy and industry perspective, robo-advisors are often promoted as mechanisms to expand access to financial services by lowering intermediation costs and minimum investment requirements, potentially making wealth management more accessible to retail investors with limited assets (Philippon, 2019).

Despite the potential benefits of robo-advisory services, empirical evidence indicates that adoption remains fragmented across global markets. This disparity is driven not only by structural market conditions but also by consumer-level factors such as trust, financial literacy, and technological self-efficacy (Eren, 2023; Gan et al., 2021). Because robo-advisors remove the human element from financial planning, an individual's psychological predisposition toward automated systems becomes a critical determinant of their decision-making process (Aw et al., 2023; Belanche et al., 2019; Piehlmaier, 2022). Consequently, understanding the diffusion of these services requires a dual focus on both broader environmental contexts and the specific psychological drivers that shape a consumer's readiness to embrace AI-driven advice.

Building on this understanding, the following section explores the specific determinants that influence consumer adoption and engagement with robo-advisory platforms.

2.1. Consumer Adoption of Robo-Advisory Services

A growing body of literature has examined the determinants of consumer adoption of robo-advisory services. Much of this research draws on established technology adoption frameworks, including the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), which have been widely applied and extended in studies of robo-advisor adoption (Belanche et al., 2019). These models consistently identify system-centric attributes—namely perceived usefulness, effort expectancy, and platform trust—as pivotal predictors of behavioural intention, while simultaneously recognising perceived risk as a primary barrier to adoption (Aw et al., 2023). This foundational focus on functional technology acceptance factors is mirrored across broader AI-enabled financial applications, including empirical evidence from banking chatbots where performance expectancy and social influence similarly govern user behaviour (Toh & Tay, 2022).

However, recent empirical developments suggest that these standardised system-related factors cannot fully account for variance in consumer behaviour on their own. Researchers have increasingly shifted focus toward how individual user characteristics interact with automated systems. For instance, Hohenberger et al. (2019) and Gan et al. (2021) highlight that intrinsic trust in algorithmic decision-making and subjective familiarity with automated wealth management heavily moderate adoption intentions. Similarly, in emerging market contexts, discrepancies in individual financial and

technological literacy act as significant barriers to adoption, even in environments with mature digital infrastructures (Piehlmaier, 2022).

These findings collectively demonstrate that consumers respond heterogeneously to identical digital interfaces based on their personal attributes, exposing a critical limitation in conventional literature. While TAM- and UTAUT-based studies provide valuable baseline insights, they overemphasise exogenous technological characteristics while underrepresenting individual psychological differences toward technology. To address this imbalance, frameworks capable of capturing idiosyncratic user predispositions, especially TRI offer a vital, complementary lens to fully understand the nuances of robo-advisory adoption.

2.2. Technology Readiness Index (TRI)

The TRI offers an alternative and complementary approach to understanding technology adoption by focusing on individuals' predispositions toward technology rather than on specific system features. Originally developed by Parasuraman (2000) and later refined by Parasuraman and Colby (2015), TRI conceptualises technology readiness as a set of beliefs that determine a person's propensity to embrace and use new technologies.

TRI comprises four dimensions: optimism, innovativeness, discomfort, and insecurity. Optimism reflects a positive view of technology and the belief that it enhances efficiency and control, while innovativeness captures an individual's tendency to be a technology pioneer. In contrast, discomfort represents feelings of being overwhelmed by technology, and insecurity reflects concerns related to reliability, privacy, and security. Optimism and innovativeness function as enablers of adoption, whereas discomfort and insecurity serve as inhibitors.

Empirical studies have applied TRI across multiple digital service contexts, including mobile banking, self-service technologies, and online platforms, demonstrating its robustness and explanatory power (Pires et al., 2024). By capturing psychological readiness that traditional acceptance models may overlook, TRI is particularly relevant in complex and high-stakes contexts such as financial decision-making and robo-advisory adoption.

2.3. Technology Readiness and Robo-Advisory Adoption

The application of the TRI to robo-advisory services has gained significant traction as researchers analyse consumer responses to AI-driven financial delegation. Unlike traditional FinTech tools (e.g., mobile banking), robo-advisory platforms require users to relinquish decision-making authority to automated algorithms. This shift often amplifies psychological barriers related to "algorithmic opacity," loss of control, and systemic trust (Parasuraman & Colby, 2015). Consequently, an individual's inherent technology readiness—a multidimensional construct comprising mental "enablers" (Optimism and Innovativeness) and "inhibitors" (Discomfort and Insecurity)—is a central determinant of adoption intention (Aw et al., 2023; Belanche et al., 2019).

Prior studies demonstrate that optimism and innovativeness act as positive drivers of behavioural intention, whereas discomfort and insecurity function as inhibiting factors that can hinder adoption even when the perceived functional benefits of technology are high (Hohenberger et al., 2019). Furthermore, Choudhary et al. (2023) and Sivathanu (2019) argued that in high-stakes financial environments, the inhibitors often exert a stronger influence than the enablers, as the perceived risk of financial loss triggers heightened insecurity toward automated systems.

The relevance of TRI is particularly pronounced in emerging markets, where consumers exhibit heterogeneous levels of digital literacy and exposure to advanced financial services. In such contexts, understanding the interplay between these psychological dimensions is critical for explaining adoption behaviour beyond conventional technology acceptance variables like perceived usefulness (Sivathanu, 2019). Thus, TRI provides a robust framework for identifying consumer segments that may be technologically ready in a general sense but psychologically resistant to AI-driven financial advice.

2.4. Awareness of Robo-Advisory Services

In addition to technology readiness, functional awareness, defined as the consumer's grasp of the existence, underlying logic, and value proposition of a platform, acts as a vital boundary condition for adoption. While individuals may exhibit high levels of technological optimism, a knowledge-readiness gap often persists; existing research indicates that general technological competence does not necessarily translate into actual usage when consumers lack a clear understanding of the service's functionality and value proposition (Eren, 2023; Gan et al., 2021). This is particularly salient in emerging markets, where latent awareness creates a cognitive barrier, preventing potential users from progressing from the initial knowledge stage to the active decision stage of the innovation-diffusion process (Eren, 2023).

In these ecosystems, awareness gaps frequently mirror institutional voids in financial literacy. Nazmi et al. (2024) argued that transparency and proactive information provision are mandatory for converting interest into action, especially among demographics with limited exposure to digital investment vehicles. Theoretically, these findings suggest that awareness performs a dual function: it enhances the perception of functional utility and, crucially, serves as a de-risking mechanism. By demystifying the "black-box" nature of AI algorithms, increased awareness directly mitigates the insecurity and discomfort dimensions identified in the TRI framework, thereby establishing the systemic trust required for automated financial delegation (Eren, 2023; Nazmi et al., 2024).

2.5. Research Gap

Although existing studies have advanced understanding of robo-advisory adoption, several gaps remain. First, much of the literature continues to rely on technology-centric models such as TAM and UTAUT, with limited integration of individual predispositions toward technology. Second, empirical studies applying the TRI to robo-advisory services remain relatively scarce, particularly in emerging market contexts. Third, the role of awareness has often been examined in isolation rather than in conjunction with technology readiness.

Accordingly, there is a need for empirical research that integrates TRI dimensions and awareness to explain consumers' intention to adopt robo-advisory services. Addressing this gap is particularly relevant in emerging markets such as Malaysia, where regulatory support and technological infrastructure coexist with uneven adoption patterns.

3. Methodology

3.1 Research Framework

Figure 1 presents the research framework, which combines the dimensions of the TRI and service awareness to explain consumers' intention to use robo-advisory services. The framework is adapted from Flavián et al. (2022).

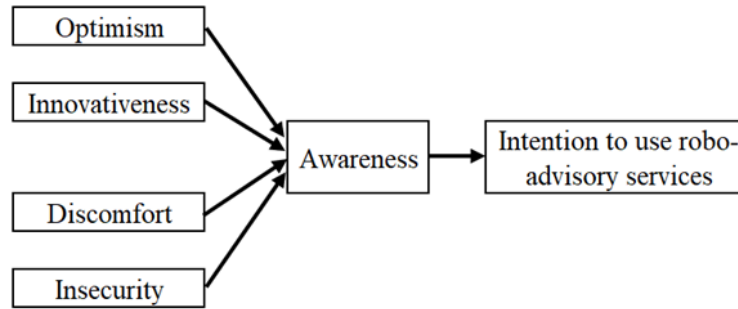


Fig. 1: Research Framework of Factors Influencing Consumers' Intention to Use Robo-Advisory Services.

Specifically, four TRI dimensions—optimism, innovativeness, discomfort, and insecurity—are modelled as direct predictors of intention to use robo-advisory services. Optimism reflects individuals' positive beliefs regarding the benefits and efficiency of technology, while innovativeness captures their propensity to be early adopters of new technological solutions. These dimensions are expected to enhance consumers' receptiveness toward robo-advisory platforms. In contrast, discomfort and insecurity represent inhibiting factors associated with perceived lack of control, complexity, and concerns over reliability and security, which may impede adoption intentions.

In addition to technology readiness, the framework incorporates awareness as a key cognitive factor influencing adoption intention. Awareness reflects individuals' knowledge and understanding of robo-advisory services, including their functionality and potential benefits. Importantly, awareness is conceptualised as a mediating mechanism through which TRI dimensions influence adoption intention. Higher levels of awareness are expected to reduce uncertainty and enhance individuals' evaluations of robo-advisory services, thereby strengthening their intention to use.

3.2 Hypothesis Development

3.2.1 Optimism and Intention to Use Robo-Advisory Services

Optimism, a core dimension of the TRI, refers to an individual's positive belief that technology enhances efficiency, control, and overall life quality (Parasuraman & Colby, 2015). Individuals with higher levels of optimism are more inclined to focus on the enabling and performance-enhancing aspects of new technologies, leading to stronger adoption intentions in digitally mediated services.

In the context of robo-advisory services, optimism is particularly salient due to the reliance on AI, algorithms, and data-driven decision-making. Optimistic consumers are more likely to perceive robo-advisors as objective, unbiased, and capable of delivering superior portfolio management outcomes compared to human advisors. This positive orientation reduces psychological resistance toward automated financial decision systems and strengthens confidence in algorithmic advice.

Empirical evidence across financial technology and AI-enabled services consistently demonstrates that optimism significantly enhances users' behavioural intention to adopt automated and intelligent systems. For instance, Belanche et al. (2019) and Hohenberger et al. (2019) show that favourable technology beliefs increase acceptance of algorithm-based recommendations by enhancing perceived usefulness and trust. Similarly, Jung et al. (2018) find that positive attitudes toward digital financial technologies significantly predict consumers' willingness to adopt robo-advisory services.

Accordingly, this study proposes the following hypothesis:

H1: Optimism has a positive effect on consumers' intention to use robo-advisory services.

3.2.2 Innovativeness and Intention to Use Robo-Advisory Services

Innovativeness reflects an individual's propensity to be a technology pioneer and a willingness to experiment with new technologies earlier than others (Agarwal & Prasad, 1998; Lu et al., 2005; Nguyen et al., 2025). Individuals with high levels of personal innovativeness are generally more open to technological uncertainty and more willing to explore novel digital solutions, such as AI products (Zhang et al., 2025). This trait aligns with the early adopter category in Diffusion of Innovations theory, in which innovators are characterised by a greater inclination to take risks and adopt innovations ahead of the majority (Rogers, 2003).

Robo-advisory services represent a disruptive financial innovation that departs from traditional, human-based advisory models. Innovative consumers are significantly more likely to experiment with these platforms, as their inherent openness to change and technological pioneerism help them overcome the "black box" uncertainty associated with algorithmic decision-making (Belanche et al., 2019).

Empirical evidence suggests that personal innovativeness remains a primary driver of adoption for AI-based FinTech applications, as these individuals view technological uncertainty as a challenge to be mastered rather than a threat (Aw et al., 2023). Furthermore, this trait is essential during the initial trust-building phase, acting as a psychological catalyst that enables users to develop confidence in automated financial systems and facilitates their adoption (Cao et al., 2026).

Based on this reasoning, the following hypothesis is proposed:

H2: Innovativeness has a positive effect on consumers' intention to use robo-advisory services.

3.2.3 Discomfort and Intention to Use Robo-Advisory Services

Discomfort reflects a perceived lack of control over technology and a sense of being overwhelmed by its inherent complexity (Parasuraman & Colby, 2015). In financial contexts, where decisions involve significant risk and long-term consequences, technological complexity can intensify consumers' emotional resistance, acting as a psychological barrier to engagement (Belanche et al., 2019). Robo-advisory platforms rely on sophisticated, often opaque algorithms and automated decision-making processes that may be difficult for the average retail investor to fully comprehend—a phenomenon often described as algorithmic aversion (Dietvorst et al., 2015).

Consumers experiencing high levels of discomfort may feel uneasy delegating high-stakes investment decisions to "black-box" systems, fearing a loss of agency and an inability to intervene during market volatility (Castelo et al., 2019). Prior studies applying the TRI have consistently identified discomfort as a potent inhibitor in the adoption of digital financial services and AI-enabled wealth management tools (Pires et al., 2024). In these contexts, the perceived lack of human touch can exacerbate feelings of being overwhelmed, leading to a preference for traditional human intermediaries (Boreiko & Massarotti, 2022).

Accordingly, the following hypothesis is formulated:

H3: Discomfort has a negative effect on consumers' intention to use robo-advisory services.

3.2.4 Insecurity and Intention to Use Robo-Advisory Services

Insecurity refers to distrust of technology and concerns related to reliability, privacy, and security (Parasuraman, 2000). In the context of robo-advisory services, insecurity may arise from concerns over data privacy, algorithmic transparency, and the perceived lack of human oversight in investment decisions.

Given the sensitive nature of financial information and the potential financial consequences of algorithmic errors, insecurity is expected to be a significant barrier to adoption. Empirical research in FinTech adoption consistently identifies security and trust-related concerns as major inhibitors of intention to use digital financial services (Ryu, 2018).

Accordingly, this study proposes the following hypothesis:

H4: Insecurity has a negative effect on consumers' intention to use robo-advisory services.

3.2.5 Awareness and Intention to Use Robo-Advisory Services

Awareness refers to consumers' knowledge of the existence, features, and potential benefits of robo-advisory services. In emerging markets, limited exposure to digital investment products may result in low awareness, which constrains adoption even among technologically capable individuals.

Higher awareness can reduce uncertainty, enhance perceived legitimacy, and increase confidence in robo-advisory platforms. By providing consumers with a clearer understanding of the underlying technology and regulatory safeguards, service awareness acts as a vital bridge that transforms latent interest into trust and adoption intention (Singh & Srivastava, 2018). Prior research further suggests that awareness plays a critical cognitive role in shaping adoption behaviour by enhancing perceived usefulness and reducing uncertainty associated with digital financial services (Eren, 2023). Moreover, findings by Lim et al. (2025) indicate that even among digitally native consumers, awareness remains a key determinant of adoption decisions.

Beyond its direct influence, awareness may also function as an intermediary mechanism through which individuals' technological predispositions translate into behavioural intention. Individuals with higher levels of technology readiness are more inclined to engage in information-seeking and cognitive processing of technology-related knowledge, thereby enhancing their awareness of robo-advisory services. This increased awareness, in turn, strengthens their intention to adopt such services (Flavián et al., 2022; Parasuraman & Colby, 2015), reinforcing its role as a key mediating mechanism in technology adoption processes.

Based on this reasoning, the following hypotheses are proposed:

H5: Awareness has a positive effect on consumers' intention to use robo-advisory services.

H6: Awareness mediates the relationship between TRI dimensions and intention to use robo-advisory services.

3.3 Data Collection, Instruments, and Analysis Methods

Data were collected via an online survey from Malaysian consumers aged 18 and above. Given the early diffusion stage of robo-advisory services and the absence of a sampling frame, convenience sampling was employed, consistent with prior FinTech adoption research in emerging markets (e.g., Belanche et al., 2019; Gan et al., 2021). A total of 180 usable responses were obtained.

To capture individuals' predispositions towards technology, the study employed the TRI developed by Parasuraman and Colby (2015), encompassing all four dimensions: optimism, innovativeness, discomfort, and insecurity. Following Flavián et al. (2022), the original items were slightly reworded to refer specifically to robo-advisor, ensuring relevance to the FinTech context.

Consumers' awareness of robo-advisory services was measured using a three-item scale capturing respondents' familiarity with and understanding of the service and its features. Consistent with Flavián et al. (2022), awareness is conceptualised as a cognitive condition reflecting individuals' knowledge and recognition of AI-driven financial services, and the items were contextualised to the robo-advisory setting.

The dependent variable, intention to use robo-advisory services, was measured using three items adapted from Bhattacharjee (2000), capturing respondents' willingness and likelihood to adopt such services in the near future.

The data were analysed using the Partial Least Squares Structural Equation Modelling (PLS-SEM) approach to validate the research model and test the proposed hypotheses. Following the two-step analytical procedure, the assessment first focused on the measurement model to evaluate the reliability and validity of the constructs. Internal consistency reliability was examined using Cronbach's alpha (α) and composite reliability (CR), while convergent and discriminant validity were assessed through average variance extracted (AVE) and the heterotrait–monotrait (HTMT) ratio, respectively.

Subsequently, the structural model was evaluated to examine the hypothesised relationships among the constructs. Path coefficients, significance levels, and the explanatory power of the model (R^2) were

analysed to determine the effects of optimism, innovativeness, discomfort, insecurity, and awareness on consumers' intention to use robo-advisory services.

4. Results and Discussion

4.1 Descriptive Analysis

Table 1 provides a summary of the demographic characteristics of the 180 respondents. The sample was relatively balanced in terms of gender, with a slight majority of male participants (53.33%). In terms of age distribution, the sample was predominantly composed of young adults, with those aged 18–29 representing 62.22% of the total, followed by the 30–39 age bracket (21.11%).

Regarding ethnicity, Chinese respondents constituted the majority (58.89%), followed by Malay (23.89%) and Indian (12.22%) participants. The sample was highly educated, with over half of the respondents holding or currently pursuing a bachelor's degree (56.67%) and an additional 25.56% having attained a diploma. This educational profile is consistent with the early-adopter demographic typically associated with FinTech and robo-advisory services.

Table 1: Demographic Profile of Respondents ($N = 180$)

Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	96	53.33
	Female	84	46.67
Age	18–29 years old	112	62.22
	30–39 years old	38	21.11
	40–49 years old	14	7.78
	50 years old and above	16	8.89
Ethnicity	Chinese	106	58.89
	Malay	43	23.89
	Indian	22	12.22
	Others	9	5.00
Education Level	Secondary	9	5.00
	Foundation	12	6.67
	Diploma	46	25.56
	Undergraduate Degree	102	56.67
	Postgraduate	11	6.11

4.2 Measurement Model Assessment

Prior to testing the structural model, the psychometric properties of all reflective constructs were evaluated following the two-step procedure recommended by Anderson and Gerbing (1988) and the PLS-SEM guidelines of Hair et al. (2019). The measurement model was assessed in terms of indicator reliability, internal consistency reliability, convergent validity, and discriminant validity.

Indicator reliability. Indicator reliability was assessed by inspecting the standardised outer loadings of all reflective indicators. As presented in Table 2, all items returned loadings above the minimum acceptable threshold of 0.70 (Hair et al., 2019), ranging from 0.71 to 0.91. These values confirm that each indicator shares a sufficient proportion of variance with its corresponding latent construct.

Internal consistency reliability. Internal consistency was evaluated using both α and CR. As shown in Table 2, CR values ranged from 0.80 to 0.92, all exceeding the recommended threshold of 0.70 (Nunnally & Bernstein, 1994). Cronbach's alpha values ranged from 0.63 to 0.86. Although the alpha for Insecurity ($\alpha = 0.63$) falls marginally below the conventional 0.70 cut-off, Hair et al. (2019) note that CR is the more appropriate reliability index in PLS-SEM and that alpha may be overly

conservative for constructs with few items; the CR of 0.80 confirms acceptable reliability for this construct.

Convergent validity. Convergent validity was assessed using AVE. All six constructs achieved AVE values exceeding the 0.50 threshold established by Fornell and Larcker (1981), ranging from 0.54 to 0.79 (Table 2). These results confirm that each construct accounts for a majority of the variance in its indicators, thereby demonstrating adequate convergent validity.

Table 2: Measurement Model: Outer Loadings, Cronbach's Alpha, Composite Reliability, and Average Variance Extracted

Construct	Items	Factor Loadings	α	CR	AVE
Optimism (OP)	OP1–OP4	0.71–0.76	0.71	0.82	0.54
Innovativeness (INO)	INO2–INO4	0.73–0.85	0.71	0.84	0.64
Discomfort (DIS)	DIS1–DIS4	0.86–0.88	0.83	0.90	0.75
Insecurity (INS)	INS1–INS4	0.71–0.81	0.63	0.80	0.58
Awareness (AW)	AW1–AW3	0.87–0.91	0.86	0.92	0.79
Intention to Adopt (INT)	INT1–INT3	0.86–0.90	0.84	0.91	0.76

Note. CR = composite reliability; AVE = average variance extracted; α = Cronbach's alpha. All factor loadings are standardised. $N = 180$.

Discriminant validity. Discriminant validity was assessed using the HTMT (Henseler et al., 2015), which is preferred over the Fornell–Larcker criterion due to its superior sensitivity in detecting discriminant validity violations (Voorhees et al., 2016). As reported in Table 3, all HTMT values ranged from 0.00 to 0.69, well below the conservative threshold of 0.90 and also satisfying the more stringent HTMT_{0.85} criterion, thereby confirming that all constructs are empirically distinct.

Table 3: Discriminant Validity: Heterotrait-Monotrait Ratio of Correlations (HTMT)

Construct	(1)	(2)	(3)	(4)	(5)	(6)
1. Optimism	—					
2. Innovativeness	0.60	—				
3. Discomfort	0.10	0.00	—			
4. Insecurity	0.21	0.35	0.47	—		
5. Awareness	0.45	0.62	0.29	0.32	—	
6. Intention	0.54	0.66	0.08	0.30	0.69	—

Note. HTMT values obtained from 5,000 bootstrap resamples (Henseler et al., 2015). All values are below the 0.85 conservative threshold. Diagonal not applicable (—). Absolute values reported.

Common method bias and collinearity assessment. Common method bias was assessed using Harman's single-factor test; the unrotated factor solution yielded a single dominant factor accounting for 28.4% of total variance, well below the 50% threshold, suggesting that common method bias is unlikely to constitute a serious threat to the validity of the findings (Podsakoff et al., 2003).

Collinearity was assessed at two levels in accordance with the PLS-SEM guidelines of Hair et al. (2019): outer VIF values (indicator-level collinearity within each construct) and inner VIF values (construct-level collinearity among predictors in each structural equation). In PLS-SEM, a VIF value

below 3.3 is considered indicative of negligible collinearity; values exceeding 5.0 signal a potential collinearity problem (Hair et al., 2019; Ringle et al., 2015).

Table 4 presents the outer VIF values for all 19 indicators across the six constructs. All values ranged from 1.21 to 2.67, substantially below the threshold of 3.3. These results confirm that no indicator-level multicollinearity is present within any construct, and that all items contribute distinct variance to their respective latent variables.

Table 5 presents the inner VIF values for predictor constructs in both structural equations (Awareness and Intention as endogenous variables). All inner VIF values ranged from 1.16 to 1.50, well within acceptable bounds. These results confirm the absence of multicollinearity among the predictor constructs and validate the independence of the estimated path coefficients reported in Table 6.

Table 4: Outer VIF Values: Indicator-Level Collinearity Assessment

Construct	Indicator	VIF	Assessment
Optimism	OP1	1.54	No collinearity concern
	OP2	1.47	No collinearity concern
	OP3	1.26	No collinearity concern
	OP4	1.28	No collinearity concern
Innovativeness	INO2	1.56	No collinearity concern
	INO3	1.42	No collinearity concern
	INO4	1.32	No collinearity concern
Discomfort	DIS1	1.77	No collinearity concern
	DIS3	2.11	No collinearity concern
	DIS4	2.02	No collinearity concern
Insecurity	INS1	1.25	No collinearity concern
	INS2	1.21	No collinearity concern
	INS4	1.28	No collinearity concern
Awareness	AW1	2.23	No collinearity concern
	AW2	2.67	No collinearity concern
	AW3	2.04	No collinearity concern
Intention to Adopt	INT1	2.32	No collinearity concern
	INT2	1.93	No collinearity concern
	INT3	1.92	No collinearity concern

Note. VIF = variance inflation factor. Outer VIF computed by regressing each indicator on all remaining indicators within its construct. Threshold for concern: $VIF > 3.3$ (Hair et al., 2019). All values indicate negligible collinearity. $N = 180$.

Table 5: Inner VIF Values: Construct-Level Collinearity Assessment for Structural Equations

Predictor Construct	VIF ($\rightarrow$ Awareness)	VIF ($\rightarrow$ Intention)	Assessment
Optimism	1.24	1.30	No collinearity concern
Innovativeness	1.28	1.50	No collinearity concern
Discomfort	1.16	1.20	No collinearity concern
Insecurity	1.22	1.23	No collinearity concern
Awareness	—	1.44	No collinearity concern

Note. VIF = variance inflation factor. Inner VIF computed by regressing each predictor construct on the remaining predictor constructs within each structural equation. Threshold for concern: $VIF > 3.3$ (Hair et al., 2019). (—) = construct not included as predictor in that equation. All values indicate negligible multicollinearity. $N = 180$.

4.3 Structural Model Assessment

Having confirmed the adequacy of the measurement model, the structural model was assessed by examining standardised path coefficients (β), bootstrapped standard errors (SE), t -statistics, two-tailed p -values, and bias-corrected 95% confidence intervals derived from 5,000 bootstrap resamples (Hair et al., 2019). All structural model results are reported in Table 6.

Awareness emerged as the strongest predictor of adoption intention ($\beta = 0.40$, $SE = 0.06$, $t = 6.75$, $p < .01$, 95% CI [0.23, 0.56]), underscoring its pivotal role as a proximal antecedent of behavioural intention in the Malaysian robo-advisory context. This finding suggests that the primary barrier to adoption is not attitudinal resistance, but a deficit of functional understanding regarding the underlying logic and value proposition of these platforms. This finding corroborates the arguments of Bihari et al. (2026) and Eren (2023), who emphasise that insufficient functional understanding constitutes a primary obstacle to FinTech adoption in emerging market settings.

Optimism ($\beta = 0.20$, $p = .03$) and innovativeness ($\beta = 0.22$, $p < .01$) both demonstrated significant direct effects on adoption intention, reaffirming the enabling role of positive technology readiness orientations in AI-driven financial service adoption. In other words, consumers who perceive technology as a tool for efficiency and those who possess a natural propensity for experimentation are primary drivers of the initial diffusion stage of robo-advisory adoption.

Notably, discomfort also exerted a significant positive direct effect on adoption intention ($\beta = 0.14$, $SE = 0.05$, $t = 2.89$, $p < .01$, 95% CI [0.05, 0.22]). While this positive relationship between discomfort and adoption intention may appear counterintuitive given the traditional conceptualisation of discomfort as an inhibitor (Parasuraman & Colby, 2015), it aligns with the complexity–quality heuristic identified by Sivathanu (2019) and provides contextual support for the discomfort paradox proposed by Flavián et al. (2022), whereby perceived technological complexity may be interpreted as a signal of professionalism and rigour in high-stakes financial service contexts.

Insecurity did not significantly predict adoption intention ($\beta = -0.10$, $p = .13$), a finding that contrasts with Choudhary et al. (2023) but may reflect the contextual normalisation of digital financial services in Malaysia, where widespread adoption of digital banking and electronic payment systems has potentially attenuated data security concerns as an impediment to newer FinTech services (Parasuraman, 2000).

Table 6: Structural Model Results: Standardised Path Coefficients, Standard Errors, and Bootstrapped Confidence Intervals

Hypothesised Path	β	SE	t	p	95% Boot CI	Decision
Optimism $\rightarrow$ Awareness	0.31	0.11	2.77	<.01	[0.08, 0.58]	Supported
Innovativeness $\rightarrow$ Awareness	0.49	0.09	5.43	< .01	[0.28, 0.69]	Supported
Discomfort $\rightarrow$ Awareness	-0.16	0.06	-2.61	.01	[-0.28, -0.04]	Supported
Insecurity $\rightarrow$ Awareness	-0.08	0.09	-0.91	.36	[-0.30, 0.10]	Not Supported
Awareness $\rightarrow$ Intention	0.40	0.06	6.75	< .01	[0.23, 0.56]	Supported
Optimism $\rightarrow$ Intention	0.20	0.09	2.26	.03	[0.01, 0.43]	Supported
Innovativeness $\rightarrow$ Intention	0.22	0.08	2.91	<.01	[0.05, 0.40]	Supported
Discomfort $\rightarrow$ Intention	0.14	0.05	2.89	<.01	[0.05, 0.22]	Not Supported
Insecurity $\rightarrow$ Intention	-0.10	0.07	-1.52	.13	[-0.25, 0.05]	Not Supported

Note. β = standardised path coefficient; SE = standard error; t = t -statistic derived from 5,000 bootstrap resamples; 95% Boot CI = bias-corrected bootstrapped confidence interval. $N = 180$.

4.4 Assessment of Explanatory Power (R^2) and Predictive Relevance (Q^2)

To evaluate the structural model's performance, the coefficient of determination (R^2) and the Stone-Geisser blindfolding metric (Q^2) were assessed for all endogenous constructs. The R^2 value measures the model's explanatory power by calculating the proportion of variance in the endogenous variables explained by their structural antecedents.

Table 7: Coefficient of Determination (R^2), Adjusted R^2 , and Predictive Relevance (Q^2)

Endogenous Variable	R^2	Adjusted R^2	Q^2	Effect Size
Awareness	0.31	0.29	0.18	Moderate
Intention to Adopt	0.46	0.44	0.30	Substantial

Note. Effect size classification follows Hair et al. (2019): $R^2 \geq 0.25$ = moderate; $R^2 \geq 0.50$ = substantial. $Q^2 > 0$ indicates out-of-sample predictive relevance (Stone-Geisser criterion). $N = 180$.

As detailed in Table 7, the model accounts for 31% of the variance in Awareness ($R^2 = 0.31$, Adjusted $R^2 = 0.29$). According to the thresholds established by Hair et al. (2019), this indicates a moderate explanatory effect size, confirming that individual technology readiness traits (drivers and inhibitors) explain a meaningful portion of consumer service familiarity. More crucially, the model demonstrates high explanatory power regarding behavioural outcomes, accounting for 46% of the total variance in Intention to Adopt ($R^2 = 0.46$, Adjusted $R^2 = 0.44$). This approaches the substantial threshold (≥ 0.50) designated by Hair et al. (2019), showing that the combined structural pathways—mediated through technology awareness—offer a robust framework for anticipating consumer adoption intentions in algorithmic financial landscapes. To assess the out-of-sample predictive validity of the structural framework, a blindfolding procedure with an omission distance of seven ($D = 7$) was executed to obtain the Q^2 values. Following the Stone-Geisser criterion, Q^2 values greater than zero indicate that the model possesses non-trivial predictive relevance for the specific endogenous constructs under evaluation (Henseler et al., 2015). The blindfolding results yield a Q^2 value of 0.18 for Awareness and 0.30 for Intention to Adopt. Because both values are substantially

above zero, the findings provide strong empirical confirmation of the structural model's predictive capability, verifying its reliability for strategic forecasting in the retail robo-advisory domain.

4.5 Mediation Analysis

The mediating role of awareness between the four TRI dimensions and adoption intention was examined using bias-corrected bootstrapped indirect effects (5,000 resamples), as recommended by Preacher and Hayes (2008) and Zhao et al. (2010). Mediation is established when the bootstrapped 95% confidence interval for the indirect effect excludes zero. The classification of mediation type follows Zhao et al. (2010): partial mediation is indicated when both the indirect and direct effects are statistically significant; full mediation is indicated when only the indirect effect is significant.

As presented in Table 8, awareness significantly mediates the effect of optimism on adoption intention ($\beta = 0.25$, $SE = 0.07$, $t = 3.54$, $p < .01$, 95% CI [0.13, 0.41]). Because the direct path from optimism to intention also remained significant, partial mediation is established. This pattern suggests that while optimistic technology orientations directly foster adoption intentions, they also operate indirectly by enhancing informational engagement with robo-advisory services, consistent with the receptivity-to-awareness pathway theorised by Belanche et al. (2019). Similarly, awareness partially mediates the effect of innovativeness on adoption intention ($\beta = 0.25$, $SE = 0.06$, $t = 4.01$, $p < .01$, 95% CI [0.14, 0.38]). The significance of this indirect pathway reinforces Flavián et al.'s (2022) argument that experimentally-oriented individuals are more likely to seek out and process information about novel financial technologies before forming adoption intentions.

Awareness also significantly mediates the relationship between discomfort and adoption intention, yielding a significant negative indirect effect ($\beta = -0.09$, $SE = 0.04$, $t = -2.26$, $p = .02$, 95% CI [-0.17, -0.01]). Given that the direct effect of discomfort on intention remains significant and positive, this pattern reflects inconsistent partial mediation, whereby discomfort reduces adoption indirectly through diminished awareness while concurrently exerting a positive direct effect on intention. (Flavián et al., 2022). This nuanced finding warrants careful theoretical interpretation and is discussed further in Section 5.

Finally, awareness fully mediates the effect of insecurity on adoption intention ($\beta = -0.15$, $SE = 0.07$, $t = -2.27$, $p < .01$, 95% CI [-0.30, -0.04]), as the direct effect of insecurity on intention was non-significant ($\beta = -0.10$, $p = .13$). This pattern suggests that insecurity influences adoption intention exclusively through its dampening effect on awareness, rather than through any direct attitudinal pathway. This finding is consistent with the technology normalisation thesis (Parasuraman, 2000), wherein security concerns operate as background cognitive constraints that reduce informational engagement rather than directly suppressing behavioural intentions in populations accustomed to digital financial services.

Table 8: Mediation Analysis: Bootstrapped Indirect Effects of Technology Readiness Dimensions on Adoption Intention via Awareness

Indirect Path	β	SE	t	p	95% Boot CI	Mediation Type
Optimism $\rightarrow$ Awareness $\rightarrow$ Intention	0.25	0.07	3.54	< .01	[0.13, 0.41]	Partial
Innovativeness $\rightarrow$ Awareness $\rightarrow$ Intention	0.25	0.06	4.01	< .01	[0.14, 0.38]	Partial
Discomfort $\rightarrow$ Awareness $\rightarrow$ Intention	-0.09	0.04	-2.26	.02	[-0.17, -0.01]	Partial
Insecurity $\rightarrow$ Awareness $\rightarrow$ Intention	-0.15	0.07	-2.27	.02	[-0.30, -0.04]	Full

Note. Indirect effects derived from 5,000 bias-corrected bootstrap resamples (Preacher & Hayes, 2008). Mediation type follows Zhao et al. (2010): partial = both direct and indirect effects significant; full = only indirect effect significant. CI = confidence interval. $N = 180$.

5. Conclusion

This study examines consumer intention to adopt robo-advisory services by integrating the TRI dimensions with awareness as a mediating mechanism. The findings provide important insights into how individual predispositions and cognitive engagement jointly shape intention of adoption in an emerging FinTech context.

A central finding is the pivotal role of awareness, which emerges as the strongest predictor of adoption intention while also functioning as a key mediating mechanism. This indicates that intention is constrained more by limited understanding than by resistance to technology. In this regard, intention of adoption can be viewed as a two-stage process, in which technology readiness influences individuals' engagement with information, which subsequently drives behavioural intention. This underscores the importance of cognitive engagement as a fundamental pre-condition for the diffusion of AI-driven financial services.

The enabling dimensions of TRI—optimism and innovativeness—exert both direct and indirect effects on adoption intention. Individuals who perceive technology as beneficial and who are inclined toward experimentation are more likely to engage with and adopt robo-advisory platforms. This dual influence highlights the combined role of favourable attitudes and proactive information-seeking in shaping early-stage adoption decisions.

More nuanced insights emerge from the roles of discomfort and insecurity. Discomfort negatively influences awareness, suggesting that perceived complexity reduces engagement with robo-advisory information. However, it simultaneously exerts a positive effect on adoption intention, indicating that technological complexity may be interpreted as a signal of sophistication and professional capability in financial contexts. This finding suggests that discomfort does not function purely as an inhibitor but exerts stage-specific effects across the adoption process. In contrast, insecurity does not directly influence intention but operates indirectly by limiting awareness, indicating that security concerns primarily reduce informational engagement rather than actively discouraging adoption.

These findings carry several managerial implications. The centrality of awareness suggests that robo-advisory providers should prioritise educational strategies that enhance users' understanding of platform functionality. Communication efforts should emphasise clarity, transparency, and accessibility, supported by tools such as interactive demonstrations and simplified explanations of algorithmic processes. At the same time, the significance of innovativeness highlights the importance of offering

features that encourage exploration and personalisation. The dual role of discomfort further suggests that platform design should balance usability and sophistication, ensuring ease of access without undermining perceived credibility.

From a policy perspective, the results highlight the importance of promoting digital investment literacy as part of broader financial education initiatives. Regulatory efforts should focus on improving transparency in areas such as algorithmic decision-making, fee structures, and data governance, thereby facilitating awareness formation and strengthening public confidence in AI-driven financial services.

Despite its contributions, this study has several limitations. The use of a convenience sample limits the generalisability of the findings across different demographic groups. In particular, the sample is skewed toward younger respondents and is predominantly Chinese, which does not fully reflect the Malaysian population, where Bumiputera groups constitute the majority and older age groups hold a larger share of investment assets. As such, the findings should be interpreted with caution and cannot be generalised to Malaysian consumers as a whole. The cross-sectional design also restricts the ability to examine changes in perceptions over time, suggesting the need for longitudinal research. In addition, the model focuses primarily on individual-level factors and does not incorporate other relevant constructs such as social influence, trust, or perceived risk. Future research could extend the framework by integrating these factors and exploring their interaction with technology readiness and awareness. Finally, comparative studies across different national contexts would provide further insight into the generalisability of the findings and the role of institutional and cultural factors in shaping adoption behaviour.

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