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AI ADOPTION IN MALAYSIA'S FINANCIAL SERVICES SECTOR: EXTENDING THE TECHNOLOGY ACCEPTANCE MODEL WITH COST AND SYSTEM QUALITY DIMENSIONS

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Abstract

Malaysian financial service providers—particularly those operating outside the mainstream banking sector—have been slow to integrate Artificial Intelligence into their core operations, despite compelling evidence of its transformative potential in financial management, credit assessment, and risk control. To illuminate the specific forces that shape this reluctance, the present study develops and tests an augmented version of the Technology Acceptance Model that incorporates two underexplored determinants: System Quality and operational Costs. Survey data gathered from 384 microfinance operators spanning Malaysia's northern, central, and southern regions were subjected to Partial Least Squares Structural Equation Modeling. Every postulated relationship achieved statistical significance. Cost proved to be the dominant driver of adoption intention ($\beta = 0.402$, $p < 0.001$), trailed by Perceived Usefulness ($\beta = 0.253$, $p < 0.001$), System Quality ($\beta = 0.056$, $p < 0.001$), and Perceived Ease of Use ($\beta = 0.034$, $p < 0.001$). Together these predictors account for 78.4 percent of variance in adoption intention—an exceptional yield by IS research standards. The ascendancy of Cost over traditionally dominant constructs represents a theoretically noteworthy departure from patterns documented in technologically mature markets, pointing instead toward the structural economic constraints unique to small financial businesses in an emerging market setting. The paper closes with concrete guidance for FinTech solution providers, regulatory authorities, and financial institution managers seeking to narrow Malaysia's AI adoption gap.

Keywords: AI Adoption, Financial Services, Technology Acceptance Model, System Quality, Cost Sensitivity, FinTech, Malaysia, PLS-SEM, Microfinance, Emerging Markets.

I. INTRODUCTION

A. Setting the Scene

Few sectors have felt the disruptive weight of digitalization more acutely than financial services. Lenders, insurers, asset managers, and payment processors are harnessing Artificial Intelligence to accomplish in milliseconds what previously required days of manual effort—from parsing loan applications to flagging anomalous transactions and constructing bespoke investment portfolios. The underlying technologies, ranging from classical statistical machine learning to deep neural architectures, share a common property: they improve with exposure to data, making finance an especially fertile domain because financial institutions accumulate transactional records at extraordinary scale (Arner, Barberis, & Buckley, 2016).

Within Southeast Asia, enthusiasm for financial technology has been pronounced. Malaysia occupies an intermediate position—more digitally advanced than many regional peers yet still grappling with uneven adoption across the spectrum of financial service providers. Bank Negara Malaysia signalled the strategic importance of digital financial infrastructure in its Financial Sector Blueprint 2022–2026, which explicitly identifies AI as a cornerstone

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technology for the coming decade (BNM, 2021). Notwithstanding this institutional backing, ground-level uptake among smaller operators remains conspicuously thin.

Non-bank financial providers—credit cooperatives, microfinance companies, and salary-advance services—collectively extend credit to segments of the population that mainstream banks frequently decline to serve. Roughly fifteen percent of Malaysian adults remain without a formal bank account (World Bank, 2021), making the question of AI adoption in this sub-sector a matter of public interest as well as commercial relevance (Ozili, 2018).

B. The Problem This Study Addresses

The rate of AI adoption among Malaysia's non-bank financial operators falls well short of what both policy ambition and commercial logic would suggest. Several plausible explanations circulate in practitioner discourse—expense, technical complexity, data scarcity, and regulatory ambiguity each feature regularly—but systematic empirical examination of which factors matter most, and by how much, is largely absent from the academic literature.

Much of the extant FinTech adoption research was conducted in developed-economy contexts where the cost of digital infrastructure is proportionally modest relative to organisational revenues. Extrapolating those findings to Malaysian microfinance risks producing recommendations systematically miscalibrated for a context defined by tight margins, heterogeneous workforce skills, and variable connectivity (Alzubi et al., 2018).

C. Research Questions

Four specific questions orient the empirical work:

- RQ1: To what extent does Perceived Ease of Use shape the adoption intention of Malaysian financial service providers regarding AI systems?
- RQ2: How strongly does Perceived Usefulness predict that adoption intention?
- RQ3: What role does perceived System Quality play in determining whether providers intend to adopt AI?
- RQ4: How does the anticipated cost burden of AI implementation influence adoption intention?

D. Aims and Contributions

The overarching aim is to produce a rigorously validated, context-sensitive account of AI adoption determinants that moves beyond generic technology acceptance theory to reflect the economic and infrastructural realities of Malaysia's non-bank financial sector. Theoretically, the study enriches TAM literature by demonstrating that Cost and System Quality are central predictors capable of reshaping the classical PU–PEOU hierarchy. Practically, it furnishes FinTech developers, regulators, and institutional managers with a ranked, quantified picture of the barriers they must address.

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II. REVIEW OF LITERATURE AND CONCEPTUAL FRAMEWORK

A. Technology Acceptance Theory: From TAM to Its Extensions

When Davis (1989) published the Technology Acceptance Model, the central contribution was elegance: a two-construct theoretical account—Perceived Usefulness and Perceived Ease of Use—that could reliably predict whether individuals would choose to use a new information system. The model drew intellectual ancestry from Fishbein and Ajzen's (1975) Theory of Reasoned Action. Meta-analytic work confirmed that TAM performs robustly across industries, national cultures, and technological generations (King & He, 2006; Legris, Ingham, & Collerette, 2003).

As AI systems entered organisational life, limitations in the original TAM became apparent. The model says relatively little about the material conditions surrounding adoption—the quality of the underlying technical infrastructure, the financial resources required to implement and sustain a system, or the broader institutional environment. Venkatesh et al. (2003) partially addressed such concerns through UTAUT, and Venkatesh and Davis (2000) introduced TAM2 to capture social influence effects. The present study contributes by incorporating System Quality and Cost as additional constructs tailored to an emerging market context.

B. AI Applications in Financial Services

AI's footprint across financial services spans four broad operational domains. In client-facing roles, recommendation engines personalise investment advice and chatbots handle routine queries around the clock. Risk and compliance functions have benefited most dramatically: ML models identify fraudulent patterns with a speed no human analyst can replicate, and natural language processing automates the extraction of relevant clauses from regulatory filings (Arner et al., 2016). Back-office automation targets document processing and reconciliation workflows, while emerging RegTech applications help institutions navigate complex compliance landscapes proactively.

These gains are well documented in large institutional settings, but the picture for smaller operators is more complicated. Microfinance firms typically hold narrower datasets, lack in-house technical talent, and operate on margins that leave little room for speculative technology investment. In Malaysia specifically, this translates to a sector where enthusiasm for AI may be genuine but where structural barriers repeatedly defer actual implementation (Ozili, 2018).

C. Perceived Usefulness

Across the TAM literature, Perceived Usefulness consistently emerges as the stronger of the two original predictors (King & He, 2006). In the AI context, usefulness perceptions hinge on whether staff believe the system will meaningfully improve credit-risk decisions, reduce processing times, or cut fraud losses—concrete outcomes that resonate with operators whose survival depends on tight operational control. Prior research in Malaysian banking (Ramayah & Ignatius, 2005) and adjacent Asian markets (Gefen & Straub, 2000) confirms that PU retains its predictive strength across cultural contexts.

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D. Perceived Ease of Use

Ease of Use is by no means trivial, particularly in the early stages of technology diffusion when operators have little hands-on familiarity with a system (Venkatesh & Davis, 2000). AI platforms introduce a distinctive complexity: their decision logic is often opaque, outputs are probabilistic, and configuration frequently requires collaboration with technical specialists. In a workforce where digital competencies vary considerably, perceptions of ease of use can constitute a genuine psychological barrier even when a system's usefulness is broadly acknowledged (Jahangir & Begum, 2008).

E. System Quality

System Quality—encompassing reliability, processing accuracy, response latency, data security, and interface navigability—has been theorised as a foundational prerequisite for IS success since DeLone and McLean's (2003) landmark IS Success Model reformulation. A system that crashes unpredictably, produces inaccurate outputs, or responds unacceptably slowly will deter adoption regardless of affordability or conceptual utility. Al-Mushasha and Hassan (2009) formalised this relationship in a mobile learning context; Li and Yeh (2009) documented analogous patterns in telecommunications. For Malaysian microfinance operators who depend on AI outputs for real-time credit decisions, reliability and accuracy are operational necessities.

F. Cost as a Structural Barrier

Cost in the technology adoption context is multi-layered: software licensing, hardware upgrades required to run AI workloads, labour investment in staff training, consulting fees for customisation, and ongoing maintenance expenditure (Wu & Wang, 2005; Chiu & Wang, 2008). For a microfinance firm operating on a net interest margin of two or three percent, even a modest monthly SaaS fee represents a material proportion of discretionary budget. Khalifa and Shen (2006) observed comparable dynamics in mobile commerce adoption, finding that cost sensitivity elevated sharply among organisations with limited liquidity—a pattern that resonates strongly with the operators studied here.

G. Research Hypotheses

Drawing on the foregoing conceptual scaffolding, four directional hypotheses are advanced:

H1: Perceived Ease of Use exerts a positive and statistically significant influence on the intention of Malaysian financial service providers to adopt AI systems.

H2: Perceived Usefulness exerts a positive and statistically significant influence on that adoption intention.

H3: System Quality exerts a positive and statistically significant influence on adoption intention.

H4: Cost perceptions exert a positive and statistically significant influence on adoption intention.

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III. METHODOLOGY

A. Philosophical Stance and Study Design

The study is anchored in a post-positivist tradition, reflecting the conviction that social phenomena can be meaningfully studied through systematic quantification and hypothesis testing. A cross-sectional survey design was selected as the most efficient vehicle for gathering comparable data across a geographically dispersed population within a defined data-collection window (Saunders, Lewis, & Thornhill, 2019). The analytic approach is descriptive and correlational: the goal is to estimate the strength and direction of relationships among theoretical constructs.

B. Target Population, Sampling, and Recruitment

Registered microfinance businesses operating in Peninsular Malaysia comprised the target population. Drawing on enterprise registries from AIBIM and AKPK, the reachable population was estimated at 27,000 firms. Reference to Krejcie and Morgan's (1970) sampling tables indicated that 384 responses would provide adequate precision at a ninety-five percent confidence level with a five-percent error margin.

The peninsula was partitioned into three zones—northern (Kedah, Perlis, Penang, Perak), central (Selangor, Kuala Lumpur, Putrajaya, Negeri Sembilan), and southern (Johor, Melaka)—with a proportionate stratum drawn from each. Questionnaires were administered through online forms and printed instruments between March and June 2023. Of 384 distributed, 378 were returned in a condition suitable for analysis, yielding a sixty-eight percent effective response rate—satisfying the fifty-percent benchmark that survey researchers typically regard as acceptable (Hair et al., 2019).

C. Measurement Instrument

The questionnaire was structured in two parts. Demographic information was collected in the opening section. The substantive portion measured five latent constructs via established Likert-scaled items, each anchored at one (strongly disagree) and five (strongly agree).

- Perceived Ease of Use: 4 items from Davis (1989). Representative item: "Becoming proficient with an AI-based financial system would not require excessive effort on my part."
- Perceived Usefulness: 4 items from Davis (1989). Representative item: "Deploying AI in our financial processes would enhance the overall performance of my organisation."
- System Quality: 4 items from Abbitt (2006). Representative item: "The AI financial platform I would use is dependable and consistently delivers correct outputs."
- Costs: 3 items from Wu and Wang (2005). Representative item: "The total financial outlay required to introduce and maintain an AI financial system is acceptable given expected returns."
- Adoption Intention: 4 items from Venkatesh et al. (2003). Representative item: "My organisation plans to incorporate AI-driven financial tools within the coming year."

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Expert review by three academic specialists and two senior industry practitioners confirmed content adequacy. A pilot study involving forty-five non-sample operators produced Cronbach alpha values above 0.80 for each construct before full deployment.

D. Analytical Procedure

Preliminary data handling was performed in IBM SPSS v22. Hypothesis testing relied on PLS-SEM executed in SmartPLS 2.0 (Ringle, Wende, & Will, 2005). PLS-SEM was preferred over its covariance-based counterpart because it tolerates mild non-normality in Likert-scale data, suits models with moderate sample sizes, and prioritises explanatory variance aligned with this study's predictive orientation (Hair et al., 2019). Reliability and validity of the measurement model were confirmed before structural paths were estimated, following Anderson and Gerbing's (1988) recommended two-stage procedure.

IV. FINDINGS

A. Who Responded: Sample Characteristics

The 378 usable respondents skewed moderately male (53.2%) and were concentrated in the 26–30-year age bracket (45.0%). Nearly three-fifths held at least a bachelor's degree (58.2%), and a further 18.5 percent had completed postgraduate study. The largest single tenure group (52.4%) reported between four and seven years of hands-on experience with financial information systems. Full demographic frequencies appear in Table 1.

Table 1: Sample Demographic Profile (N = 378)

Characteristic	Category	Frequency	Percentage (%)
Gender	Male	201	53.2
	Female	177	46.8
Age	21–25 years	89	23.5
	26–30 years	170	45.0
	31–40 years	98	25.9
	41+ years	21	5.6
Education	Diploma	88	23.3
	Bachelor's Degree	220	58.2
	Postgraduate	70	18.5
Experience	1–3 years	72	19.0
	4–7 years	198	52.4
	8+ years	108	28.6

B. Measurement Model: Reliability and Validity

All five constructs satisfied standard psychometric benchmarks. Composite reliability values ranged from 0.841 to 0.967, each above the required 0.70 (Hair et al., 2019). Average Variance Extracted ranged from 0.606 to 0.939, clearing the 0.50 floor set by Fornell and Larcker (1981). Discriminant validity was established via the Fornell-Larcker criterion and corroborated by Heterotrait-Monotrait ratios below the conservative 0.85 ceiling recommended by Henseler et al. (2015). Tables 2 and 3 present full results.

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Table 2: Reliability and Convergent Validity Indicators

Construct	Items	Loadings Range	CR	α	AVE
PEOU	4	0.712–0.891	0.873	0.821	0.632
PU	4	0.756–0.934	0.921	0.897	0.743
SQ	4	0.698–0.912	0.884	0.841	0.657
Cost	3	0.841–0.978	0.967	0.961	0.939
Adoption Intention	4	0.721–0.918	0.912	0.877	0.724

Table 3: Fornell-Larcker Discriminant Validity Matrix (diagonal = √AVE)

	PEOU	PU	SQ	Cost	Adoption
PEOU	**0.795**	**0.621**	**0.543**	**0.418**	**0.512**
PU	**0.621**	**0.862**	**0.589**	**0.476**	**0.631**
SQ	**0.543**	**0.589**	**0.811**	**0.502**	**0.558**
Cost	**0.418**	**0.476**	**0.502**	**0.969**	**0.634**
Adoption	**0.512**	**0.631**	**0.558**	**0.634**	**0.851**

C. Structural Model and Hypothesis Tests

Bootstrap resampling with 5,000 iterations generated the standard errors and t-statistics used to evaluate path significance. The model accounts for 78.4 percent of variance in adoption intention ($R^2 = 0.784$). An SRMR of 0.062—below the recommended 0.08 ceiling (Hu & Bentler, 1999)—corroborated adequate model fit. All four hypotheses were supported, as detailed in Table 4.

Table 4: Structural Path Estimates and Hypothesis Outcomes

Hypothesis	Path	β	Std. Error	t-Value	p-Value	Verdict
H1	PEOU → Adoption	0.034	0.004	8.406	<0.001	Supported
H2	PU → Adoption	0.253	0.017	14.819	<0.001	Supported
H3	SQ → Adoption	0.056	0.008	6.933	<0.001	Supported
H4	Cost → Adoption	0.402	0.070	5.743	<0.001	Supported

D. Common Method Variance Assessment

Harman's exploratory factor test returned a largest unrotated factor explaining 29.3 percent of total variance—well within the fifty-percent threshold that signals serious inflation (Podsakoff et al., 2003). Full-collinearity diagnostics produced Variance Inflation Factor values between 1.34 and 2.87, all below Kock's (2015) ceiling of 3.3. Neither test raised grounds for concern.

V. DISCUSSION

A. Cost as the Dominant Gatekeeper

Perhaps no finding is more consequential—or theoretically provocative—than Cost at the top of the predictor hierarchy (β = 0.402). In TAM's original conceptualisation, usefulness commands the largest path coefficient and economic factors are typically relegated to the status of background moderators. This study inverts that ordering decisively, with Cost exerting an influence on adoption intention nearly sixty percent larger than that of Perceived Usefulness and more than ten times that of Perceived Ease of Use.

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This inversion is not anomalous when the study population is examined carefully. Microfinance operators run businesses where net margins are measured in single-digit percentages and access to affordable long-term credit for capital investment is structurally limited. Against that backdrop, the multi-layered cost profile of an AI implementation—licensing, infrastructure, training, customisation, ongoing support—appears genuinely prohibitive. Khalifa and Shen (2006) documented an analogous pattern in mobile commerce adoption among resource-constrained users. For FinTech developers, this crystallises a strategic imperative: pricing architecture is a fundamental design constraint, not a downstream commercial decision.

B. Usefulness: The Persuasive Core

With a standardised coefficient of 0.253 and the highest t-statistic in the model (14.819), Perceived Usefulness occupies second position while exhibiting the most statistically precise estimate. This precision reflects genuine convergence in respondents' assessments of AI's performance potential: where operators believed AI would materially improve credit accuracy, accelerate processing, or reduce fraud losses, adoption intention rose sharply. The consistency of this effect across a heterogeneous sample reinforces what TAM researchers have documented for decades (King & He, 2006): usefulness is a universal motivator regardless of context.

C. System Quality: The Floor, Not the Ceiling

System Quality registered a coefficient of 0.056—statistically significant but modest relative to Cost and Usefulness. System quality functions as a threshold condition rather than a continuous motivator: below an acceptable quality floor, adoption intention collapses; above it, incremental improvements yield diminishing returns on adoption probability. This reading is consistent with DeLone and McLean's (2003) IS Success Model, which positions system quality as a prerequisite for IS success rather than its primary engine. AI platform developers should invest in robust offline functionality, strong security architectures, and dashboards calibrated to users with moderate technical literacy.

D. Perceived Ease of Use: Relevant but Not Rate-Limiting

The smallest path coefficient ($\beta = 0.034$) belongs to Perceived Ease of Use, though with a t-statistic of 8.406 it retains clear statistical significance. This ranking is consistent with broader TAM literature showing that PEOU's influence erodes as familiarity with a technology class accumulates (Venkatesh & Davis, 2000). Respondents averaging four to seven years of experience with financial information systems may already have internalised general patterns of software interaction, making specific AI interface navigability less salient than cost or demonstrated performance. This finding counsels against deprioritising UX investment while cautioning against treating ease of use as the primary adoption lever.

E. Model-Level Synthesis

Viewed in aggregate, the extended TAM model explains seventy-eight percent of variance in adoption intention—substantially exceeding the forty to sixty percent range commonly reported in standard TAM FinTech applications. This gain is attributable, at least in part, to the

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inclusion of Cost and System Quality as explicit constructs rather than as latent noise. The implication for future IS adoption research is clear: when studying technology adoption in emerging markets characterised by resource constraints and infrastructure variability, the classical TAM framework should be regarded as a starting point rather than a complete specification.

VI. CONCLUSION

A. Principal Findings

This study set out to identify and quantify the factors most powerfully shaping the willingness of Malaysian microfinance operators to adopt AI-driven financial systems. An extended TAM framework enriched with System Quality and Cost constructs, tested against survey data from 378 operators through PLS-SEM, yielded support for all four hypotheses. Cost ($\beta = 0.402$) proved to be the paramount influence, followed by Perceived Usefulness ($\beta = 0.253$), System Quality ($\beta = 0.056$), and Perceived Ease of Use ($\beta = 0.034$). The collective explanatory power ($R^2 = 0.784$) substantially exceeds benchmarks from comparable adoption studies.

B. Theoretical Significance

Three theoretical advances merit recognition. First, the extended TAM incorporating economic and infrastructural constructs substantially outperforms the standard two-construct specification in emerging market contexts. Second, the displacement of Perceived Usefulness from the top of the predictor hierarchy by Cost provides the most direct empirical evidence to date that economic rationality can dominate cognitive ease preferences when resource constraints are sufficiently severe. Third, by grounding findings in the Malaysian non-bank financial sector, the study opens a productive research stream the literature has largely overlooked.

C. Recommendations

For FinTech Developers: Pricing architecture is a first-order design decision. Architectures that minimise hardware dependency, usage-proportional billing models, and feature-capped entry tiers calibrated to microfinance revenue profiles would each address the cost barrier identified as the dominant adoption constraint. Multilingual interfaces designed for moderate literacy levels would simultaneously address the PEOU dimension.

For Policymakers: Bank Negara Malaysia should consider targeted tax relief on qualifying AI technology expenditures, co-financing arrangements through development finance institutions, regulatory sandbox mechanisms that permit AI trials under reduced compliance costs, and nationally coordinated digital upskilling programmes reaching rural and semi-urban operator workforces.

For Financial Institution Managers: Invest in structured internal pilots that produce auditable evidence of AI's operational impact—documented reductions in loan processing times, measurable improvements in default prediction, or quantified fraud savings. Such evidence strengthens the internal usefulness case identified as the second most powerful adoption driver.

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D. Limitations and Future Research

Three limitations warrant acknowledgement. The cross-sectional design captures intention at a single point, precluding assessment of whether intentions translate into actual adoption behaviour—a gap that longitudinal panel studies could address. Geographic coverage is limited to Peninsular Malaysia; dynamics in Sabah and Sarawak may yield a different predictor hierarchy. And while the model explains a high proportion of variance, it does not incorporate organisational-level moderators—firm age, size, ownership structure, competitive intensity—that plausibly amplify or dampen identified relationships.

Future researchers might pursue multi-wave panel designs linking adoption intention to verified adoption behaviour. Comparative cross-national work within ASEAN—benchmarking Malaysia against Singapore's mature FinTech environment and Indonesia's comparably resource-constrained context—would test whether Cost primacy is Malaysia-specific or a broader feature of emerging market AI adoption. Qualitative complements, including interviews with adopters and explicit non-adopters, would enrich understanding of the mechanisms through which cost perceptions crystallise into adoption barriers.

E. Closing Statement

The headline message of this study is direct: for Malaysian microfinance operators, the question of whether to adopt AI is answered first through a cost-benefit lens, and only secondarily through assessments of utility or usability. This reframes the policy challenge. Improving AI platform user interfaces or demonstrating predictive power in pilot trials will build adoption momentum, but neither strategy addresses the foundational economic barrier identified as primary. Closing the AI adoption gap in Malaysia's non-bank financial sector ultimately requires making AI financially accessible—through product innovation, fiscal incentives, and co-investment—not merely demonstrating that it works.

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