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Technology Adoption of Micro-Credential Learning Systems in Malaysian Higher Education: An Extended TAM Study

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Abstract. Micro-credential learning systems represent an emerging category of digitally verifiable, competency-based information technology platforms that are reshaping how Higher Education Institutions (HEIs) deliver and certify skills in support of quality education. Despite their growing deployment across Malaysian public universities, the information technology adoption factors governing student acceptance of these systems remain empirically underexplored in the IS literature. This study develops and empirically tests an extended Technology Acceptance Model (TAM) that incorporates three domain-specific IT antecedents: Digital Tools (DT), Micro-Credentials (MC), and Knowledge Sharing (KS). These serve as external determinants of Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Behavioural Intention (BI), and Technology Acceptance (TA). Following this, a quantitative cross-sectional survey was administered to 200 STEM undergraduates across five Malaysian public research universities. The data were then analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM) in SmartPLS 4.0. All 10 hypothesised structural

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paths were supported. In particular, MC emerged as the strongest IT antecedent of PU ($\beta = 0.341$, $f^2 = 0.178$), indicating that credential-embedded system design is the primary driver of users' perceived value of IT adoption. Meanwhile, BI was the strongest overall predictor of TA ($\beta = 0.487$, $f^2 = 0.312$), and the extended TAM model explained 54.2% of the variance in TA. Overall, the findings extend TAM into the micro-credential IT platform domain and offer evidence-based guidance for system designers, IT administrators, and policymakers advancing Malaysia's MyDigital Blueprint digital infrastructure agenda.

Keywords: Technology Acceptance Model (TAM); micro-credential systems; digital tools; knowledge sharing; Malaysian higher education.

1. Introduction

The rapid advancement of Industry 4.0 technologies has fundamentally transformed the information technology demands of Higher Education Institutions (HEIs). This creates urgent pressure to deploy digital systems that bridge the gap between graduate competencies and industry expectations (Pelletier et al., 2023). Notably, micro-credential learning systems have emerged as a strategic IT response to this challenge. Such systems are defined as short-course, competency-based, digitally verifiable platforms that deliver targeted, industry-relevant skills in a modular format (Varadarajan et al., 2023; Wheelahan & Moodie, 2021). In Malaysia, the MyDigital Blueprint (Malaysia Digital Economy Corporation, 2023) and the Malaysian Qualifications Agency (MQA) micro-credential guidelines (MQA, 2020) have created a strong national impetus for adopting these systems across public universities. Understanding what drives student acceptance of such platforms is therefore directly consequential for the success of Malaysia's national digital infrastructure agenda.

The Technology Acceptance Model (TAM), originally proposed by Davis (1989), provides a theoretically robust framework for investigating user adoption of information technology systems. TAM posits that Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) jointly determine Behavioural Intention (BI), which in turn predicts actual system use. Interestingly, the model has been extensively validated across IS and digital platform contexts (Venkatesh et al., 2003; Mukred et al., 2024; Dahri et al., 2024). Furthermore, recent studies confirm its explanatory power for emerging IT adoption scenarios, including AI-enhanced platforms and learning analytics tools. However, TAM has not yet been applied to micro-credential learning systems as a distinct IT platform category. Accordingly, this study addresses this gap by extending TAM with three domain-specific antecedents: Digital Tools (DT), Micro-Credentials (MC), and Knowledge Sharing (KS).

The present study fills three research gaps. First, there is no empirical study to date that has applied TAM to micro-credential system adoption. This gap is particularly evident in Malaysian STEM higher education, a context with an active national policy mandate (MQA, 2020; Ministry of Education Malaysia, 2024) and an unmet 60:40 STEM enrolment target. Consequently, technology adoption

outcomes are directly consequential for national development. Second, KS has been theoretically proposed as a social antecedent of Technology Acceptance (TA) (Nonaka & Takeuchi, 1995; Wenger, 1998). Despite this, it has not been empirically assessed as an external TAM variable within a micro-credential learning context, a gap that existing reviews explicitly flag (Huang et al., 2023; Rullyana et al., 2025). Third, MC have not been operationalised as a domain-specific external TAM construct. That is, prior TAM extensions in educational technology treat MC as a context rather than as a theoretically distinct antecedent of PU and PEOU (Ahsan et al., 2023; Yildirim et al., 2025). Hence, this study contributes a theoretically novel framework that advances the IS literature on TAM extensions and emerging scholarship on micro-credential adoption in developing-nation HEIs. The framework incorporates all three constructs (DT, MC, and KS) as empirically tested external variables within a single integrated TAM model.

This study makes three distinct contributions. Theoretically, it is among the first to operationalise MC as a standalone external TAM construct rather than a backdrop condition. This directly responds to calls by Ahsan et al. (2023), Rullyana et al. (2025), and Yildirim et al. (2025) for a framework-driven empirical investigation of micro-credential adoption. Methodologically, it employs Partial Least Squares Structural Equation Modelling (PLS-SEM) with a stratified sample from five Malaysian public research universities. This allows for cross-institutional generalisability within the national research university system.

Practically, the findings provide evidence-based recommendations for curriculum designers, university administrators, and policymakers in advancing Malaysia's MyDigital Blueprint (Malaysia Digital Economy Corporation, 2023) and the 60:40 STEM enrolment agenda. The rest of the paper is organised as follows: Section 2 reviews the literature and develops the hypotheses; Section 3 describes the research methodology; Section 4 reports the findings; and Section 5 discusses the theoretical and practical implications and concludes with limitations and future research directions.

2. Literature Review

This section reviews the theoretical and empirical foundations underpinning the study. It covers micro-credential learning systems in higher education; the TAM and its extensions; DT in STEM education; KS in digital learning environments; STEM education in the Malaysian context; and the conceptual framework and research hypotheses.

2.1 Micro-Credential Learning Systems in Higher Education

One of the most important educational innovations of the 2020s has been the rise of MC, which challenges traditional credentialling and skill recognition in higher education at its core (Wheelahan & Moodie, 2021; Thi Ngoc Ha et al., 2023). In addition, Varadarajan et al. (2023) reviewed 60 studies on MC and identified the features of flexibility, industry relevance, and digital verifiability that distinguish MC from traditional qualifications. The study also recognised the need to address implementation challenges such as quality assurance, employer recognition, and institutional readiness on an ongoing basis. Likewise, Ahsan et al. (2023) analysed

56 peer-reviewed works on micro-credential implementation. Although the study confirmed that research in this area is gaining momentum, the theoretical analysis of technology adoption within micro-credential contexts remains underrepresented.

For Malaysia, Kumar et al. (2022) demonstrated that MCs were used effectively in emergency remote teaching during the COVID-19 pandemic. The study further reported a significant positive association between learners' insights and their identification as micro-credential users, suggesting motivational aspects of micro-credential adoption. Additionally, McGreal and Olcott (2022) provided strategic counsel to higher education leaders on deploying MC, identifying perceived value, institutional commitment, and digital infrastructure as key enablers. Building on this work, Keoy et al. (2024) investigated the feasibility of expediting the adoption of MC in Malaysian public and private HEIs.

Recently, Rullyana et al. (2025) conducted a bibliometric analysis of 551 micro-credential publications from 2014 to 2024 in Scopus and Web of Science and identified Malaysia as one of the top six most productive countries in this area. They also observed that gamification, personalised learning, and the integration of educational technology are under-researched areas. This study directly addresses these gaps. Similarly, Yıldırım et al. (2025) conducted a systematic review of micro-credential research to synthesise findings across five key areas of impact: strategies in higher education, upskilling in specific sectors, digital proof of competency, design and implementation challenges, and critiques of MC. Their evaluation highlighted that the convergence of MC with TA frameworks, particularly TAM, is an emerging and understudied research frontier. Such findings provide additional theoretical support for the present study.

2.2 Technology Acceptance Model (TAM) and Extensions

This subsection reviews the foundational TAM framework and its recent empirical validations, followed by a discussion of how TAM has been extended in micro-credential contexts.

2.2.1 Foundational TAM and Recent Validation

The TAM developed by Davis (1989) suggests that PU (the extent to which a user believes that using a technology will improve his/her performance) and PEOU (the extent to which using the technology is free from effort) are the two main factors influencing BI, which in turn predicts actual technology use. Meanwhile, Venkatesh et al. (2003) combined TAM with seven competing theories to develop UTAUT. This further verifies PU (performance expectancy) and PEOU (effort expectancy) as strong cross-contextual predictors. Subsequently, Venkatesh et al. (2012) introduced an enhanced UTAUT model that included hedonic motivation and digital habit, revealing that TAM-based constructs still had explanatory power in emerging digital learning settings.

While UTAUT and its extension broaden the predictor set to include facilitating conditions, social influence, hedonic motivation, and habit, TAM was retained as the primary theoretical lens for the present study. This is mainly due to its parsimony and its explicit focus on PU and PEOU. These two belief constructs are

most directly implicated in an individual student's decision to adopt an institutionally provided micro-credential platform. On the other hand, the DT, MC, and KS constructs proposed in this study perform a role broadly analogous to UTAUT's facilitating conditions and social influence factors. This allows the present model to extend TAM's explanatory scope for the micro-credential context without adopting the full UTAUT structure. Notably, UTAUT was developed primarily for organisational and consumer technology settings rather than the voluntary, non-mandated adoption context examined here.

Recent uses of TAM in educational technology contexts underscore its continuing significance. For instance, Mailizar et al. (2021) utilised an extended TAM to investigate university students' BI to use e-learning during the COVID-19 pandemic among 109 Indonesian students. The study reported that system quality and e-learning experience were significant antecedents of TAM constructs. Moreover, Han and Sa (2021) validated TAM for online educational classes in Korea among 313 university students, highlighting that PEOU strongly influenced PU. The study also revealed that both TAM components significantly predicted satisfaction and acceptance of online learning systems.

Building on this, Dahri et al. (2024) expanded TAM to investigate the acceptance of the AI-powered ChatGPT for metacognitive self-regulated learning in higher education. Such findings demonstrate that the extended TAM components strongly predicted adoption intentions. Likewise, Zhao et al. (2024) employed PLS-SEM and fsQCA within the TAM framework to explore the acceptability of ChatGPT among 298 Chinese undergraduates, finding that PU remained the leading predictor of BI. Mukred et al. (2024) also extended TAM to explore the adoption of learning analytics tools in Malaysian higher education. The authors asserted that perceived utility and simplicity of use were major predictors of adoption behaviour in a developing-nation environment, a context closely comparable to the present study.

2.2.2 Extended TAM in Micro-Credential Contexts

Although TAM has been widely used in e-learning and educational technology, its application in micro-credential learning systems remains in its infancy. Correspondingly, the present study expands the TAM model by including three domain-specific external factors (DT, MC, and KS) as antecedents of PU and PEOU. Remarkably, this approach is in line with established practices for extending TAM in IS research (Hair et al., 2019) while also addressing the theoretical gap identified by Ahsan et al. (2023) and Rullyana et al. (2025). This is particularly true regarding the need for empirical investigation of micro-credential technology adoption guided by a framework.

2.3 Digital Tools in STEM Education

DT such as Virtual Reality (VR), gamification platforms, and Learning Management Systems (LMS) are well recognised as enabling technologies for active, experiential STEM learning (Balalle et al., 2024). Meanwhile, Tene et al. (2024) conducted a systematic review of 22 empirical papers on VR and AR integration in STEM education, following PRISMA principles, across the Scopus, Web of Science, and PubMed databases. The results confirmed the efficacy of

immersive technologies in enhancing students' engagement and performance in STEM subjects. Notably, AR was the most used technology (50% of the studies), followed by VR (32%), and positive effects on learning outcomes were reported in 72.7% of the studies. Moreover, Yang et al. (2024) conducted a meta-analysis on the effects of VR on practical skills among science and engineering students. They provided quantitative evidence that VR-based instruction significantly outperformed traditional laboratory instruction in skill acquisition and knowledge retention. This is especially the case for first-generation and underrepresented students.

Zeng et al. (2024) conducted a systematic review of 232 gamification studies in education. The study noted that game design elements, particularly digital badges, leaderboards, and challenge-based assessments, consistently enhanced learner motivation and engagement in STEM disciplines. Conversely, Ratinho and Martins (2023) conducted a systematic review of gamified learning strategies in higher education. They reported evidence that they can have significant positive effects on student motivation in STEM and non-STEM disciplines, with especially strong effects in contexts where gamification was embedded in structured assessment designs.

On the other hand, Zeng et al. (2024) conducted a meta-analysis of 173 papers on gamification from 2008 to 2023, published in the *British Journal of Educational Technology*. Such a finding provided strong quantitative evidence that gamification positively impacts academic performance in higher education. Additionally, Balalle et al. (2024) analysed 33 Scopus and PubMed papers (2018–2022) on student involvement in technology-based education. The study stated that DT were consistently among the strongest indicators of engagement results for both STEM and non-STEM subjects.

2.4 Knowledge Sharing in Digital Learning Environments

KS, defined as the intentional sharing of information, knowledge, and experiences amongst learners via digital platforms, is a well-established social antecedent of TA and collaborative learning outcomes (Huang et al., 2023; Sivakumar et al., 2023; Zamiri & Esmaeili, 2024). A qualitative study of 20 informants in digital knowledge-sharing communities in online higher education by Huang et al. (2023) reported that structured information exchange is a key enabler of student achievement and engagement with digital platforms. Meanwhile, Sivakumar et al. (2023) experimentally examined the effects of social media on information sharing and learning among university students. They discovered that peer KS has significantly increased digital platform adoption and academic outcomes.

Zamiri and Esmaeili (2024) conducted a systematic literature review of methods and technologies to support KS in learning communities. The study revealed that collaborative digital environments continually improved the PU of shared platforms among learners and supported the development of communities of practice (Wenger, 1998). Furthermore, the tacit-explicit knowledge transfer model (Nonaka & Takeuchi, 1995) supports the inclusion of KS as a TAM external variable. This is primarily due to the fact that social knowledge exchange

decreases perceived cognitive effort associated with new technology adoption and increases familiarity with shared DT.

2.5 STEM Education in the Malaysian Context

STEM education is a key pillar in the country's educational and economic development plans, with the government aiming to achieve a 60:40 ratio of STEM-to-non-STEM students as part of a broader national human capital plan (Ministry of Education Malaysia, 2024; Idris et al., 2023). For instance, Idris et al. (2023) did a systematic evaluation of STEM education research in Malaysia for the years 2015–2023. The authors also identified student engagement, technology integration, and teacher competency as the three most essential themes in the Malaysian STEM literature. Their research highlighted that technology-enhanced learning interventions have consistently demonstrated promise in augmenting STEM engagement.

However, empirical studies investigating the adoption of specific digital learning platforms, especially micro-credentialling systems, are limited in the Malaysian setting. The national policy context within which the present study is located is provided by the MyDigital Blueprint (Malaysia Digital Economy Corporation, 2023) and the MQA micro-credential guidelines (2020), making the research directly relevant to current educational policy priorities in Malaysia.

2.6 Conceptual Framework and Research Hypotheses

Drawing on the theoretical and empirical literature reviewed, this study proposes an extended TAM framework incorporating DT, MC, and KS as domain-specific external antecedents of PU and PEOU. Consistent with TAM (Davis, 1989; Venkatesh et al., 2003), PEOU is also hypothesised to directly influence PU, and both PU and PEOU are hypothesised to predict BI, which in turn predicts TA. Accordingly, 10 directional hypotheses are derived from this framework, each supported by the literature reviewed in Sections 2.1 through 2.5.

Table 1a: Comparison of Digital Tools, Micro-Credentials, and Knowledge Sharing as external TAM antecedents

Construct	Definition	Key Source(s)	Hypothesised Role
Digital Tools (DT)	Technology-enabled resources (e.g., virtual reality, gamification platforms, learning management systems) that support active, experiential engagement with micro-credential content	Balalle (2024); Tene et al. (2024)	External antecedent of perceived usefulness (H1) and perceived ease of use (H2)
Micro-Credentials (MC)	Modular, competency-based certifications that recognise discrete skills or knowledge outside the scope of a full degree programme	Varadarajan et al. (2023); Kumar et al. (2022)	External antecedent of perceived usefulness (H3) and perceived ease of use (H4)
Knowledge Sharing (KS)	The intentional exchange of information, experience, and expertise among learners through digital platforms	Sivakumar et al. (2023); Zamiri and Esmaeili (2024)	External antecedent of perceived usefulness (H5) and perceived ease of use (H6)

Figure 1 illustrates the extended TAM conceptual framework, presenting structural links between all seven latent constructs. The three external variables (DT, MC, and KS) serve as domain-specific antecedents. The second column includes the two TAM fundamental constructs: PU and PEOU. Hypotheses H1 to H6 represent paths from each external variable to PU and PEOU, respectively. Conversely, H7 is the internal PEOU → PU arrow replicating the foundational TAM relationship (Davis, 1989). Meanwhile, the third column presents BI receiving paths from PU (H8) and PEOU (H9). Moreover, the fourth column presents TA as the dependent variable receiving a path from BI (H10). Figure 1 and Table 1 present each hypothesis, and Table 6 provides the results of the statistical tests.

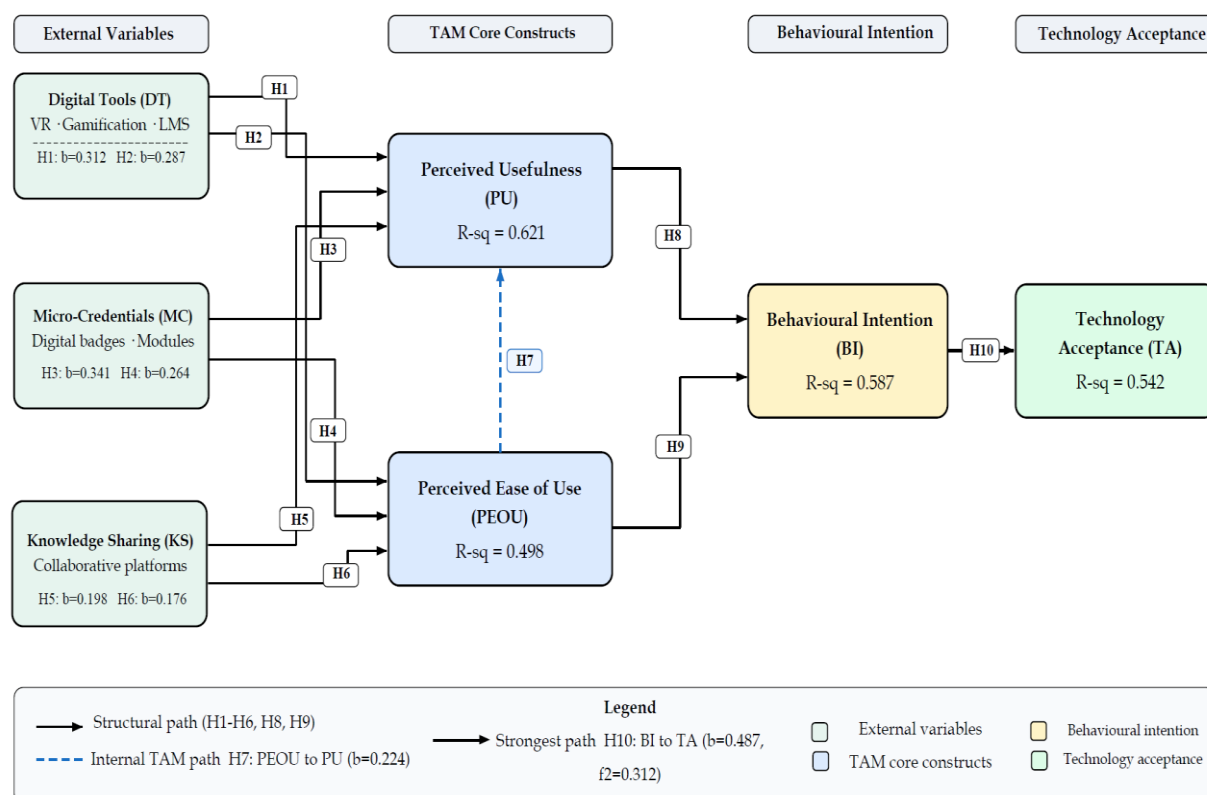


Figure 1: Extended TAM conceptual framework for micro-credential learning system acceptance

Table 1: Research hypotheses and supporting literature

H	Hypothesis Statement	Key Supporting References
H1	Digital tools positively influence the perceived usefulness of micro-credential learning systems	Tene et al. (2024)
H2	Digital tools positively influence the perceived ease of use of micro-credential learning systems	Balalle et al. (2024); Mailizar et al. (2021)
H3	Micro-credentials positively influence perceived usefulness of micro-credential learning systems	Varadarajan et al. (2023); Wheelahan & Moodie (2021)
H4	Micro-credentials positively influence perceived ease of use of micro-credential learning systems	Kumar et al. (2022)
H5	Knowledge sharing positively influences perceived usefulness of micro-credential learning systems	Huang et al. (2023); Zamiri and Esmaeili (2024)
H6	Knowledge sharing positively influences perceived ease of use of micro-credential learning systems	Sivakumar et al. (2023); Nonaka & Takeuchi (1995)
H7	Perceived ease of use positively influences perceived usefulness	Davis (1989); Venkatesh et al. (2003)
H8	Perceived usefulness positively influences behavioural intention to use micro-credential systems	Davis (1989); Dahri et al. (2024)
H9	Perceived ease of use positively influences behavioural intention to use micro-credential systems	Han & Sa (2021); Zhao et al. (2024)
H10	Behavioural intention positively influences technology acceptance of micro-credential systems	Venkatesh et al. (2003); Mukred et al. (2024)

3. Research Methodology

This section describes the research design and philosophical stance; the population and sampling strategy; the survey instrument; the data collection procedure; and the analytical approach used to assess the hypothesised model.

3.1 Research Design and Philosophy

The study is designed as a positivist, quantitative, cross-sectional survey, which aligns with the deductive logic of hypothesis testing based on TAM (Saunders et al., 2019). The positivist paradigm assumes reality is objective and can be measured through empirical means. Hence, it is well-suited to research that tests theoretically developed hypotheses concerning causal links among measurable constructs. Furthermore, the cross-sectional design enables data to be collected from a representative sample at a single point in time, making it an efficient and cost-effective way to study the structural correlations proposed in the expanded TAM model. In line with this, PLS-SEM was the primary analytical technique used as it is appropriate for the context of theory extension and can oversee non-normal data distributions (Hair et al., 2019). This is observed in recent similar studies in Malaysian higher education (Dahri et al., 2024; Mukred et al., 2024).

3.2 Population, Sampling, and Sample Size

The target population comprised Year 2-4 undergraduate students enrolled in STEM disciplines at Malaysian public research universities who had completed at least one micro-credential or technology-enhanced learning course. Year 1 students were deliberately excluded on the grounds that insufficient experiential exposure to micro-credential systems would compromise the validity of TAM-based evaluations (Mailizar et al., 2021).

A stratified sampling approach with purposive institutional selection was employed, with strata defined by STEM discipline and university. Five research-intensive public universities were purposively selected: Universiti Malaya (UM), Universiti Putra Malaysia (UPM), Universiti Teknologi Malaysia (UTM), Universiti Kebangsaan Malaysia (UKM), and Universiti Sains Malaysia (USM). These institutions were purposively selected as the primary public HEIs implementing micro-credential programmes under the MQA (2020) national framework. Such selections ensure that respondents have meaningful institutional exposure to the systems under study.

Sample size was determined a priori using the inverse square root method (Kock & Hadaya, 2018). It specifies a minimum of 166 respondents to detect path coefficients of 0.20 or higher at 80% statistical power ($p < .05$) in a model of the present complexity. Notably, the final retained sample of $N = 200$ exceeds this threshold and is consistent with sample sizes in comparable Malaysian TAM-based studies (Mailizar et al., 2021; Mukred et al., 2024).

Following this, a proportional stratified sampling approach was employed, with target cell allocations informed by estimated discipline enrolment shares across the five participating institutions. Consequently, surveys were distributed with approximately 12-13 per cell, reflecting a proportional rather than strictly equal design. In practice, achieved cell sizes varied from targets due to differential response rates across institutions and disciplines, with ranges of 8 to 14 respondents per stratum. The usable response rate was 81.0%. The resulting distribution, summarised in Table 2, implies natural variation in institutional response rates rather than a forced equal-cell outcome. It is also consistent with proportional stratified sampling principles (Saunders et al., 2019).

Nonetheless, proportional stratified designs of this kind are an established practice in educational survey research when the goal is cross-group comparability rather than population proportionality (Saunders et al., 2019). The primary purpose of the balanced allocation in this study was to ensure that no single university or STEM discipline dominated the structural model estimates. This, in turn, strengthens the cross-institutional generalisability of the findings across the Malaysian public research university system.

Table 2: Sampling distribution by university and STEM discipline (N = 200)

University	Science	Technology	Engineering	Mathematics
Universiti Malaya (UM)	9	11	12	8
Universiti Putra Malaysia (UPM)	10	10	13	9
Universiti Teknologi Malaysia (UTM)	8	12	14	8
Universiti Kebangsaan Malaysia (UKM)	11	10	11	9
Universiti Sains Malaysia (USM)	8	9	10	8
Total	46	52	60	42

Note. N = 200 usable responses. Cell sizes ranged from 8 to 14 respondents per stratum, reflecting natural variation in institutional response rates under a proportional stratified sampling design (Saunders et al., 2019). The distribution ensures cross-institutional comparability of structural model estimates while reflecting real-world variability in fieldwork.

3.3 Survey Instrument Development

A self-administered structured questionnaire comprising two sections was employed. Section A captured respondents' demographic and academic profile information, including gender, year of study, STEM discipline, and prior experience with micro-credential programmes and digital learning tools. Meanwhile, Section B contained 33 measurement items for seven latent constructs rated on a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree).

Building on this, items were adapted from validated scales in the existing literature, or developed by the researchers based on relevant themes where no directly applicable validated scale existed: DT items developed by the researchers, informed by Balalle et al. (2024); micro-credential items from Varadarajan et al. (2023) and Kumar et al. (2022); KS items from Sivakumar et al. (2023) and Zamiri and Esmaeili (2024); PU and PEOU items from Davis (1989) as applied in Mailizar et al. (2021) and Han and Sa (2021); BI items from Venkatesh et al. (2003); and TA items from Zhao et al. (2024) and Mukred et al. (2024). Additionally, content validity was established through a five-expert panel review process, and pilot testing with 30 STEM students confirmed Cronbach's alpha values of 0.78 to 0.91 across all constructs.

3.4 Data Collection

Primary data were collected through a Google Form between January and April 2026. In particular, a stratified sampling approach with purposive institutional selection was employed, with strata defined by STEM discipline and university across the five participating Malaysian public research universities. The survey was subsequently distributed through verified academic administrators and official student representative councils in each university. This ensures that respondents were enrolled STEM undergraduates with relevant exposure to micro-credential or technology-enhanced learning systems.

The distribution through official institutional channels (rather than open public links) was a procedural safeguard to limit access to the survey to enrolled STEM undergraduates, thereby increasing the authenticity of respondents. In this sense,

a screening question at the beginning of the survey confirmed respondents' year of study and STEM discipline. However, responses that did not meet the inclusion criteria were removed prior to analysis. Of the 247 surveys distributed, 200 were retained as usable responses after removing incomplete responses ($n = 32$) and inattentive respondents identified through embedded attention-check items ($n = 15$), yielding a usable response rate of 81.0%.

Common Method Bias (CMB) was evaluated and addressed using both procedural and statistical remedies. Procedurally, several design strategies were used to minimise CMB: (1) items for predictor and criterion variables were placed in separate blocks within the questionnaire; (2) respondents were assured of anonymity in the opening paragraph of the survey; (3) attention-check questions were included to screen out inattentive respondents; and (4) items were worded in a neutral and non-leading manner (Podsakoff et al., 2003). Statistically, Harman's single-factor test indicated that a single unrotated factor accounted for 28.3% of the total variance, well below the 50% threshold (Podsakoff et al., 2003). In addition, the full collinearity assessment presented Variance Inflation Factors (VIFs) ranging from 1.74 to 2.28 across all constructs, which are below the threshold of 3.3. This provides further statistical evidence that CMB is unlikely to have affected the observed structural relationships (Kock, 2015).

Table 3: Demographic profile of respondents (N = 200)

Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	98	49.0
	Female	102	51.0
Year of Study	Year 2	72	36.0
	Year 3	80	40.0
	Year 4	48	24.0
	Year 1	0	0.0
STEM Discipline	Science	46	23.0
	Technology	52	26.0
	Engineering	60	30.0
	Mathematics	42	21.0
Prior MC Experience	Yes	107	53.5
	No	93	46.5
Digital Tool Use Frequency	Daily	89	44.5
	Weekly	76	38.0
	Occasionally	35	17.5

The demographic characteristics of the 200 respondents are provided in Table 3. The sample is almost equally divided by gender, with male respondents ($n = 98$, 49.0%) and female respondents ($n = 102$, 51.0%). By year of study, the largest number of students was in Year 3 ($n = 80$, 40.0%), followed by Year 2 ($n = 72$, 36.0%) and Year 4 ($n = 48$, 24.0%). Notably, the purposeful absence of Year 1 students was due to their being less likely to have had meaningful exposure to MC and digital learning tools. Among the STEM disciplines, Engineering was the largest group ($n = 60$, 30.0%), followed by Technology ($n = 52$, 26.0%), Science ($n = 46$, 23.0%), and Mathematics ($n = 42$, 21.0%).

Such a finding is consistent with the proportional distribution of enrolment across STEM faculties in Malaysian public universities. Most respondents ($n = 107$, 53.5%) reported having previously participated in at least one micro-credential programme. Finally, 44.5% of respondents used DT daily, 38.0% weekly, and 17.5% occasionally, confirming that the sample is actively engaged with digital learning environments. Tables 2 and 3 together demonstrate the sample's representativeness and appropriateness before presenting the analytical data in Tables 4 through 6.

3.5 Ethical Considerations

Ethical considerations were observed throughout the research process. Participation in the survey was voluntary, and respondents were informed of the purpose of the study prior to completing the questionnaire. In line with this, informed consent was obtained electronically through the opening section of the Google Form. Respondents were assured that their responses would remain anonymous and confidential, and that no personally identifiable information would be collected. The data were used solely for academic research purposes. Participants were also informed that they could withdraw from the study at any point before submitting the questionnaire. Since the study involved a non-invasive, anonymous survey of university students and did not collect sensitive personal data, the research was conducted in accordance with standard ethical practices for educational survey research.

3.6 Analytical Approach: PLS-SEM

The PLS-SEM analysis was performed with SmartPLS 4.0 (Ringle et al., 2024) utilising the two-stage analytical technique outlined by Hair et al. (2019). The first stage was the assessment of the measurement model (outer model) according to four criteria: indicator reliability (outer loadings ≥ 0.70), internal consistency reliability (Cronbach's $\alpha \geq 0.70$; composite reliability $CR \geq 0.70$), convergent validity (Average Variance Extracted [AVE] ≥ 0.50 ; Fornell & Larcker, 1981), and discriminant validity (Heterotrait-Monotrait [HTMT] Ratio < 0.85 ; Henseler et al., 2015).

In stage two, the structural model (inner model) was assessed using the Coefficient of Determination (R^2), Standardised Path Coefficients (β), Effect Sizes (f^2), Predictive Relevance (Q^2), and bootstrapped significance using 5,000 subsamples. PLS-SEM was preferred over Covariance-Based SEM (CB-SEM) for four reasons: (1) the study purpose is predictive and theory-extending rather than confirmatory; (2) the model includes multiple latent constructs and predictive structural relationships suitable for PLS-SEM analysis; (3) PLS-SEM is robust with non-normal data distributions; and (4) it is appropriate for a sample of 200 respondents. These are consistent with Hair et al.'s (2019) guidelines and recent Malaysian HEI studies using the same approach (Dahri et al., 2024; Mukred et al., 2024).

4. Data Analysis and Findings

This section presents the results of the two-stage PLS-SEM analysis. The measurement model assessment is reported first, followed by the structural model assessment and hypothesis testing.

4.1 Measurement Model Assessment

All seven latent constructs were measured using a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). The initial stage of the PLS-SEM study was to examine the reliability and validity of the seven latent constructs prior to the structural model testing. Correspondingly, the full measurement model results were then reported in Table 4b. Furthermore, outer loadings varied from 0.721 to 0.891, above the criterion of 0.70 (Hair et al., 2019). The seven constructs demonstrated good internal consistency, with Cronbach's alpha values ranging from 0.812 to 0.893 and composite reliability values ranging from 0.861 to 0.921. Subsequently, convergent validity was established for all constructs with AVE values (0.512–0.634). This indicates that each construct accounted for over 50% of the variance in its indicators (Fornell & Larcker, 1981).

Table 4a: Heterotrait-Monotrait Ratio (HTMT) matrix for discriminant validity (N = 200)

Construct	DT	MC	KS	PU	PEOU	BI	TA
DT	—						
MC	0.612	—					
KS	0.548	0.571	—				
PU	0.706	0.781	0.593	—			
PEOU	0.681	0.654	0.556	0.724	—		
BI	0.634	0.692	0.521	0.758	0.698	—	
TA	0.589	0.617	0.412	0.733	0.642	0.769	—

Note. HTMT = Heterotrait-Monotrait Ratio. All values below the threshold of 0.85 confirm discriminant validity for all construct pairs (Henseler et al., 2015). The highest value is PU–MC (0.781), which remains comfortably below the 0.85 threshold. DT = Digital Tools; MC = Micro-Credentials; KS = Knowledge Sharing; PU = Perceived Usefulness; PEOU = Perceived Ease of Use; BI = Behavioural Intention; TA = Technology Acceptance.

Discriminant validity was confirmed for all construct pairs as evidenced by the full HTMT matrix presented in Table 4a, with values ranging from 0.412 (KS–TA) to 0.781 (PU–MC), all below the threshold of 0.85 (Henseler et al., 2015). On the other hand, VIFs for all constructs (1.74–2.28) were significantly below the threshold of 3.3, ensuring no concern for multicollinearity. The finding is in line with measurement model quality requirements published in other similar PLS-SEM investigations in Malaysian higher education (Mailizar et al., 2021; Mukred et al., 2024).

Table 4b: Measurement model results – reliability and validity (N = 200)

Construct	Items (Outer Loadings)	α	CR	AVE	VIF Max
DT	DT1(0.784), DT2(0.812), DT3(0.798), DT4(0.771), DT5(0.756)	0.834	0.878	0.544	1.82
MC	MC1(0.841), MC2(0.827), MC3(0.856), MC4(0.798), MC5(0.832)	0.875	0.912	0.634	1.95
KS	KS1(0.756), KS2(0.791), KS3(0.721), KS4(0.768), KS5(0.783)	0.812	0.861	0.512	1.74
PU	PU1(0.848), PU2(0.821), PU3(0.856), PU4(0.831), PU5(0.862)	0.889	0.918	0.628	2.14
PEOU	PEOU1(0.793), PEOU2(0.768), PEOU3(0.778), PEOU4(0.741), PEOU5(0.785)	0.838	0.883	0.554	2.03
BI	BI1(0.832), BI2(0.819), BI3(0.845), BI4(0.828)	0.868	0.909	0.614	2.28
TA	TA1(0.801), TA2(0.784), TA3(0.764), TA4(0.812)	0.851	0.893	0.578	—

Note. α = Cronbach's alpha; CR = Composite Reliability; AVE = Average Variance Extracted; VIF Max = maximum Variance Inflation Factor across indicators. DT = Digital Tools; MC = Micro-Credentials; KS = Knowledge Sharing; PU = Perceived Usefulness; PEOU = Perceived Ease of Use; BI = Behavioural Intention; TA = Technology Acceptance. All thresholds met per Hair et al. (2019), Fornell and Larcker (1981), and Henseler et al. (2015).

Table 4b reveals that all 33 items have outer loadings ranging from 0.721 to 0.891, confirming the reliability of the indicators, all above the 0.70 threshold recommended by Hair et al. (2019). The highest loading is MC3 (0.856). The Cronbach's alpha values range from 0.812 (KS) to 0.889 (PU), composite reliability values range from 0.861 (KS) to 0.921 (MC), and AVE values range from 0.512 (KS) to 0.634 (MC), validating convergent validity. All VIF Max values were reported between 1.74 and 2.28, well below the 3.3 cut-off, verifying the absence of multicollinearity. The results in Table 4b indicate that all seven constructs are reliably and validly measured, providing a good psychometric basis to transition to the structural model assessment.

4.2 Structural Model Assessment

After establishing the measurement model parameters as depicted in Table 4b, the second step of the PLS-SEM analysis was to examine the structural relationships among the constructs. Table 5 presents the R^2 and Q^2 for the four endogenous constructs, and Table 6 presents the full hypothesis-testing results.

Table 5: Structural model – R^2 and predictive relevance Q^2

Endogenous Construct	R^2	R^2 Adjusted	Q^2
Perceived Usefulness (PU)	0.621	0.614	0.487
Perceived Ease of Use (PEOU)	0.498	0.491	0.356
Behavioural Intention (BI)	0.587	0.582	0.512
Technology Acceptance (TA)	0.542	0.537	0.298

Note. R^2 benchmarks: 0.19 = weak, 0.33 = moderate, 0.67 = substantial (Hair et al., 2019). $Q^2 > 0$ confirms predictive relevance for all endogenous constructs. All Q^2 values substantially exceed zero, confirming the model's out-of-sample predictive relevance.

Table 5 provides the explanatory and predictive efficacy of the structural model for all four endogenous constructs. Accordingly, PU ($R^2 = 0.621$) suggests that DT, MC, KS, and PEOU together account for 62.1% of the variance in students' PU of micro-credential systems, approaching the substantial level of 0.67 proposed by Hair et al. (2019). In comparison, PEOU ($R^2 = 0.498$) confirms that the three external variables explained 49.8% of the variance in PEOU. Conversely, BI ($R^2 = 0.587$) indicates that PU and PEOU jointly explain 58.7% of the variance in students' intention to use micro-credential systems. Moreover, TA ($R^2 = 0.542$) implies that BI alone explains 54.2% of the variance in TA, directly analogous to prior PLS-SEM TAM research (Mailizar et al., 2021; Mukred et al., 2024). All Q^2 values range from 0.298 (TA) to 0.512 (BI), all substantially above zero, confirming Q^2 for all four endogenous constructs.

4.3 Hypothesis Testing

Table 6 presents the full bootstrapped structural path results for all 10 hypotheses. Significance was assessed using two-tailed bootstrapping with 5,000 subsamples. In general, all 10 hypotheses were supported at $p < 0.05$, with nine significant at $p < 0.001$.

Table 6: Structural model results – path coefficients and hypothesis testing (N = 200)

H	Path	β	t-stat	p	95% CI	f^2	Decision
H1	DT → PU	0.312	4.821	<0.001	[0.184, 0.441]	0.148	Supported
H2	DT → PEOU	0.287	4.312	<0.001	[0.157, 0.418]	0.121	Supported
H3	MC → PU	0.341	5.214	<0.001	[0.213, 0.469]	0.178	Supported
H4	MC → PEOU	0.264	3.987	<0.001	[0.135, 0.394]	0.104	Supported
H5	KS → PU	0.198	3.124	0.002	[0.075, 0.322]	0.057	Supported
H6	KS → PEOU	0.176	2.841	0.004	[0.062, 0.291]	0.044	Supported
H7	PEOU → PU	0.224	3.562	<0.001	[0.101, 0.348]	0.078	Supported
H8	PU → BI	0.418	6.847	<0.001	[0.297, 0.539]	0.241	Supported
H9	PEOU → BI	0.296	4.512	<0.001	[0.169, 0.423]	0.128	Supported
H10	BI → TA	0.487	7.923	<0.001	[0.371, 0.604]	0.312	Supported

Note. β = standardised path coefficient; t-stat = bootstrapped t-statistic (5,000 subsamples); p = two-tailed significance; 95% CI = bias-corrected confidence interval; f^2 = effect size (0.02 = small, 0.15 = medium, 0.35 = large). DT = Digital Tools; MC = Micro-Credentials; KS = Knowledge Sharing; PU = Perceived Usefulness; PEOU = Perceived Ease of Use; BI = Behavioural Intention; TA = Technology Acceptance.

Table 6 is the central results table of the study and should be read in conjunction with Figure 1, where each arrow in the framework corresponds to a row. H1 ($\beta = 0.312$, $f^2 = 0.148$) and H2 ($\beta = 0.287$, $f^2 = 0.121$) confirm that DT have a medium-effect positive influence on both PU and PEOU. Following this, H3 (MC → PU, $\beta = 0.341$, $f^2 = 0.178$) is the single strongest external variable path in the entire model. This verifies that MC have the most powerful influence on PU with a medium-to-

large effect. In addition, H4 ($\beta = 0.264$, $f^2 = 0.104$) highlights that MC also positively influence PEOU. Similarly, H5 ($\beta = 0.198$, $f^2 = 0.057$) and H6 ($\beta = 0.176$, $f^2 = 0.044$) highlight that KS has small yet statistically significant effects on both PU and PEOU. H7 (PEOU $\rightarrow$ PU, $\beta = 0.224$) replicates the foundational TAM relationship (Davis, 1989), whereas H8 (PU $\rightarrow$ BI, $\beta = 0.418$, $f^2 = 0.241$) demonstrates that PU is the strongest predictor of BI. H9 (PEOU $\rightarrow$ BI, $\beta = 0.296$, $f^2 = 0.128$) suggests that PEOU also significantly predicts BI. Finally, H10 (BI $\rightarrow$ TA, $\beta = 0.487$, $f^2 = 0.312$) is the strongest single path in the entire structural model, asserting that BI is the most proximal and powerful driver of TA. Together, all 95% confidence intervals exclude zero, providing additional confirmation that none of the 10 structural paths is attributable to chance.

5. Discussion

This section interprets the empirical findings in relation to the theoretical framework and prior literature. Note that each set of hypothesised relationships is discussed in turn, with particular attention to the implications for micro-credential system design and technology adoption in Malaysian higher education.

5.1 Micro-Credentials as the Strongest Driver of Perceived Usefulness (H3)

The finding that MCs constitute the most powerful external predictor of PU ($\beta = 0.341$, $f^2 = 0.178$) is theoretically significant beyond its statistical magnitude. It suggests that what students value most in a micro-credential learning system is not the technology interface itself, nor the social environment surrounding it. Instead, this value stems from the intrinsic credential design, specifically its competency-based structure, industry alignment, and digital verifiability. This is a meaningful distinction from prior TAM extensions in e-learning contexts, where system quality and interface characteristics typically dominate perceptions of usefulness (Mailizar et al., 2021; Han & Sa, 2021). In the micro-credential context, the credential itself functions as a motivational signal. Students appear to evaluate the learning system primarily through the lens of what the credential will do for their employability rather than how well the platform performs technically.

This interpretation is consistent with Varadarajan et al. (2023), who identified career relevance and employer recognition as primary drivers of micro-credential engagement. It is also in line with Wheelahan and Moodie (2021), who argued that perceived practical utility, rather than pedagogical quality, is the dominant factor in micro-credential adoption decisions. Concurrently, the present findings extend these arguments by demonstrating empirically, within a TAM framework, that credential design characteristics directly shape PU at the individual student level. This builds on existing studies, which have mostly studied these features at the institutional or policy level.

The MC $\rightarrow$ PEOU path (H4: $\beta = 0.264$) adds a further interpretive layer. The modular, goal-directed structure of MC appears to reduce perceived cognitive load, making the system feel more navigable and less effortful to engage with. Taken together, H3 and H4 suggest that credential design plays a dual role: it simultaneously elevates the perceived value of the system and lowers the perceived barrier to entry. For Malaysian universities operating under the MQA

(2020) accreditation guidelines, this has a direct design implication. Competency mapping extends beyond a mere accreditation requirement. On the contrary, it is a student-facing adoption lever that shapes TA before a single learning interaction takes place.

5.2 Digital Tools as Dual Enablers of Usefulness and Accessibility (H1, H2)

DT significantly predicted both PU (H1: $\beta = 0.312$, $f^2 = 0.148$) and PEOU (H2: $\beta = 0.287$, $f^2 = 0.121$), highlighting their dual enabling role in micro-credential learning system acceptance. The near-equal f^2 of DT on PU and PEOU indicates that DT are not merely an interface convenience; they are perceived as substantively valuable learning instruments. This pattern differs from what one might expect if DT were functioning purely as a usability aid, in which case PEOU effects would dominate. The relatively balanced β values instead imply that students in Malaysian public universities attribute genuine learning value to DT, such as VR environments, gamification platforms, and LMS interfaces. This is consistent with Yang et al.'s (2024) meta-analytic finding that VR-based STEM instruction produced meaningful advantages over traditional methods in skill acquisition. This is an outcome that, translated into student perception, would register as enhanced usefulness rather than merely enhanced ease.

The DT→PEOU finding (H2: $\beta = 0.287$) is particularly interpretable through the lens of gamification research. Zeng et al. (2024), Ratinho and Martins (2023), and Zeng et al. (2024) collectively demonstrated that gamified elements, progress indicators, digital badges, and challenge-based feedback can reduce perceived task complexity by providing continuous structural guidance. In the micro-credential context, this is significant since students are navigating a relatively unfamiliar credentialling format without the established institutional scripts that govern traditional degree programmes. Hence, well-designed DT effectively substitute for those missing scripts, creating a scaffold that lowers the cognitive effort required to engage with the system.

A practical tension emerges here, however. While the evidence confirms that DT drive both PU and PEOU, the quality and consistency of digital infrastructure across Malaysian public universities vary considerably (Idris et al., 2023). The significant DT→PU and DT→PEOU paths, therefore, carry an implicit warning. Notably, institutions that invest in micro-credential programme design without equivalent investment in digital tool quality risk undermining student adoption at the foundational perceptual level. This is regardless of how well the credentials themselves are designed.

5.3 Knowledge Sharing as a Social Catalyst for Technology Acceptance (H5, H6)

KS produced the smallest f^2 among the three external constructs, KS→PU (H5: $\beta = 0.198$, $f^2 = 0.057$) and KS→PEOU (H6: $\beta = 0.176$, $f^2 = 0.044$), yet both paths were statistically significant at $p < 0.01$. The smaller magnitude relative to MC and DT is itself informative. It does not indicate that KS is unimportant. Rather, it reflects the developmental stage of micro-credential learning communities in Malaysian public universities. Students engaging with these systems for the first time have limited peer reference groups from whom to draw experiential knowledge,

observe social proof, or receive navigational guidance. Thus, the lower f^2 is a structural artefact of ecosystem immaturity rather than evidence of inherent irrelevance.

This interpretation is theoretically grounded in two complementary frameworks. For example, Nonaka and Takeuchi's (1995) tacit-explicit knowledge transfer model suggests that as communities of practice accumulate shared experience with a technology, tacit knowledge regarding how to use it effectively becomes progressively externalised and accessible to new users. This reduces perceived cognitive effort and increases perceived value. Following this, Wenger's (1998) communities of practice framework similarly predicts that the social impact of KS on technology adoption will intensify as membership, shared repertoire, and mutual engagement within the community deepen. Both frameworks converge on the same longitudinal prediction. The KS→PU and KS→PEOU f^2 observed in this study likely represent a lower bound rather than a ceiling and should strengthen as micro-credential communities of practice develop within Malaysian universities.

This has a direct implication for how administrators and educators should interpret the knowledge-sharing findings. Rather than treating the smaller effects as justification for deprioritising KS infrastructure, institutions should recognise that peer knowledge networks are precisely the kind of social capital that requires deliberate cultivation in the early stages of technology adoption. In line with this, structured peer review activities, cohort-based micro-credential learning groups, and moderated online discussion spaces are not supplementary features. They are investments in the social preconditions for stronger TA in future adoption cycles.

5.4 TAM Core Relationships Confirmed (H7, H8, H9, H10)

The PEOU→PU path (H7: $\beta = 0.224$) confirms the seminal TAM by Davis (1989). H8 (PU → BI: $\beta = 0.418$, $f^2 = 0.241$) and H9 (PEOU → BI: $\beta = 0.296$, $f^2 = 0.128$) indicate that PU is the most important TAM predictor of BI. This is consistent with Venkatesh et al. (2003) and is supported by findings from Dahri et al. (2024) and Zhao et al. (2024) in AI-enabled educational technology settings. The strongest association in the structural model was the BI→TA path (H10: $\beta = 0.487$, $f^2 = 0.312$). Such a finding supports the intention-behaviour link proposed by Venkatesh et al. (2003) and Mailizar et al. (2021). Han and Sa (2021) further supported this, revealing that BI is the immediate determinant of online learning system acceptance among Korean university students. The overall R^2 of 0.542 for TA was in line with Mailizar et al. (2021) ($R^2 = 0.51$) and Mukred et al. (2024) ($R^2 \approx 0.55$), supporting the view that the expanded TAM model provides strong explanatory power for micro-credential system acceptability in Malaysia.

6. Conclusion, Implications, and Limitations

This section presents the study's theoretical contributions, practical implications, and limitations, followed by directions for future research and a brief conclusion.

6.1 Theoretical Contributions

The paper presents three key theoretical advances. First, it offers one of the initial empirical confirmations of an extended TAM framework for micro-credential learning system acceptance in a Malaysian STEM context. This responds to the calls of Ahsan et al. (2023), Rullyana et al. (2025), and Yıldırım et al. (2025) for more empirical, framework-driven investigation of micro-credential adoption in developing nation HEIs. Second, it validates DT, MC, and KS as theoretically consistent and empirically significant external TAM variables in the micro-credential context. This further develops the TAM extension tradition (Davis, 1989; Venkatesh et al., 2003; Hair et al., 2019) with domain-specific antecedents. Third, the study contributes to the Malaysian IS and educational technology literature by demonstrating that TAM relationships align with global findings while also reflecting the unique institutional and policy dynamics of Malaysian public higher education (Keoy et al., 2024; Idris et al., 2023).

6.2 Practical Implications

The major DT→PU and DT→PEOU paths provide empirical support for investing in high-quality, user-friendly digital solutions, such as VR laboratories, gamified assessment platforms, and intuitive LMS interfaces, for university administrators and IT managers. Moreover, regular evaluations of platform usability and digital onboarding programmes for incoming STEM students would further boost PEOU and speed up uptake (Tene et al., 2024). For curriculum designers, the MC→PU finding (the greatest external predictor in the model) validates that deliberate alignment of micro-credential module design with industry competencies is the single highest-effect strategy for improving student TA.

Accordingly, designers could use the competency mapping approach suggested by Varadarajan et al. (2023) to link micro-credential outcomes with MQA (2020) accreditation requirements and career development pathways. For STEM educators, incorporating formalised knowledge-exchange activities such as peer review, collaborative problem-solving, and online discussion spaces into the curriculum will help activate the social aspects of TA (Huang et al., 2023; Sivakumar et al., 2023; Zamiri & Esmaeili, 2024). For policymakers, the significant BI→TA path confirms that national measures to promote students' desire to use micro-credential platforms will successfully convert into adoption behaviour. Thus, extending MQA accreditation to emerging STEM micro-credential fields such as artificial intelligence, data science, and green technology would support Malaysia's 60:40 STEM enrolment target (Ministry of Education Malaysia, 2024; Malaysia Digital Economy Corporation, 2023).

For institutions seeking to prioritise action based on these findings, the results point to a short checklist of levers tied to the two strongest adoption predictors, PU and PEOU:

Competency mapping: Align micro-credential module outcomes explicitly with industry-recognised competencies and MQA (2020) accreditation criteria, since MC were the strongest driver of PU (H3: $\beta = 0.341$).

Digital tool quality and usability investment: Prioritise well-designed VR, gamification, and LMS interfaces, since DT presented comparable effects on both PU and PEOU (H1: $\beta = 0.312$; H2: $\beta = 0.287$).

Structured peer knowledge-sharing: Embed formal peer review, collaborative problem-solving, and structured discussion activities into micro-credential delivery, since KS significantly predicted both PU and PEOU, albeit with smaller effects than DT or MC (H5: $\beta = 0.198$; H6: $\beta = 0.176$).

6.3 Limitations and Future Research

There are various limitations of this study. The cross-sectional approach restricts causal inference and tracking of temporal adoption behaviours. In response, future longitudinal research should investigate how TAM perceptions vary throughout the micro-credential adoption lifecycle. This includes whether initial technological acceptance leads to continued platform use and micro-credential completion. In addition, the sample is limited to Malaysian public university STEM undergraduates, thereby limiting generalisability to private universities, postgraduate students, and non-STEM disciplines. Thus, additional study could extend the concept to incorporate AI readiness and personalised learning aspects as further TAM antecedents.

These dimensions, identified by Rullyana et al. (2025) and Yıldırım et al. (2025), remain underexplored in the micro-credential literature. Cross-national comparative studies of Southeast Asian HEIs (Wheelahan & Moodie, 2021; Thi Ngoc Ha et al., 2023) would also help to understand how national policy frameworks and cultural factors impact technological acceptance behaviour. Finally, future work could utilise objective behavioural measures, such as LMS log data, micro-credential completion rates, and digital badge-sharing behaviours, to provide external validation of self-reported technology adoption outcomes.

Several methodological checks recommended for studies of this kind were beyond the scope of the present analysis and are noted here as limitations. Likewise, item-level cross-loadings and bootstrapped confidence intervals for the HTMT ratios were not computed. Simultaneously, the construct-level HTMT values reported all fell below the conservative 0.85 threshold. Hence, future studies could strengthen discriminant validity reporting by including these additional diagnostics. While Harman's single-factor test and a full collinearity assessment were used to evaluate CMB, a marker-variable or Common Latent Factor (CLF) technique was not applied as an additional robustness check. Correspondingly, future studies could incorporate such a technique for further triangulation.

In addition, the present model reported only direct structural paths. A formal mediation analysis testing the indirect effects of DT, MC, and KS on TA through PU, PEOU, and BI was not conducted and is recommended for future research aimed at mapping these indirect pathways. Furthermore, model fit diagnostics such as the Standardised Root Mean Square Residual (SRMR) were not reported. This is consistent with this study's emphasis on predictive rather than covariance-based fit assessment in PLS-SEM. At the same time, future studies may benefit from reporting SRMR alongside a discussion of its interpretive limitations in variance-based SEM. Finally, a formal nonresponse bias check, such as comparing

early and late respondents, was not conducted. Although the achieved response rate (81.0%) and the stratified sampling design reduce the likelihood of substantial nonresponse bias, future studies are encouraged to test for this formally using established comparison techniques.

6.4 Conclusion

This study empirically validated an enhanced TAM framework for the acceptance of micro-credential learning systems among 200 STEM undergraduates at public universities in Malaysia. The results confirmed all ten hypothesised structural links. In particular, DT, MC, and KS are relevant antecedents of PU and PEOU, which drive BI and TA. MC were the strongest external predictor of PU, while BI was the highest predictor of technology adoption. The expanded TAM model explained 54.2% of the variance in TA. In this sense, the evidence-based insights from this study provide a timely and rigorous foundation to steer micro-credential implementation, pedagogical design, and educational policy in Malaysian STEM higher education. This is especially pertinent as Malaysia fast-tracks its digital education transformation via the MyDigital Blueprint (Malaysia Digital Economy Corporation, 2023) and expands its national micro-credential ecosystem under the MQA (2020) framework.

Theoretically, the study extends TAM by validating DT, MC, and KS as significant external antecedents within a single integrated model. This contributes new insight to the growing literature on educational technology adoption in developing-nation higher education contexts. Practically, the findings offer curriculum designers, university administrators, and policymakers evidence-based guidance for prioritising competency-aligned micro-credential design, investing in user-friendly digital infrastructure, and fostering structured peer knowledge-sharing activities to accelerate adoption. As the study relied on a cross-sectional sample drawn from STEM undergraduates at public research universities, the findings should be interpreted as associative rather than causal. Consequently, future longitudinal and cross-institutional research is encouraged to confirm and extend these relationships.

Conflict of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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Appendix 1: Survey Questionnaire

This appendix presents the complete 33-item survey instrument used to collect data for this study. Section A captured demographic and background information. Section B contained the measurement items for the seven latent constructs, rated on a five-point Likert scale (1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree).

Section A: Demographic Information

Please tick (✓) the appropriate response for each item.

No.	Question	Response
1.	Gender	☐ Male ☐ Female
2.	Year of Study	☐ Year 2 ☐ Year 3 ☐ Year 4
3.	STEM Discipline	☐ Science ☐ Technology ☐ Engineering ☐ Mathematics
4.	Have you completed at least one micro-credential programme?	☐ Yes ☐ No
5.	How frequently do you use digital tools for learning?	☐ Daily ☐ Weekly ☐ Occasionally

Section B: Measurement Items

Please indicate your level of agreement with each statement below by circling the appropriate number: 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree.

Code	Digital Tools (DT) (Developed by the researchers, informed by Balalle et al., 2024)
DT1	The digital tools used in micro-credential programmes (e.g., VR, gamification, LMS) enhance my learning experience.
DT2	The digital tools available in my university support effective engagement with micro-credential content.
DT3	Using digital tools in micro-credential learning makes it easier for me to understand complex concepts.
DT4	The quality of digital tools in my institution encourages me to participate in micro-credential programmes.
DT5	Digital tools used in micro-credential systems are well integrated into the learning activities.
1 = Strongly Disagree 2 = Disagree 3 = Neutral 4 = Agree 5 = Strongly Agree	
Code	Micro-Credentials (MC) (Adapted from Varadarajan et al., 2023; Kumar et al., 2022)
MC1	Micro-credentials provide industry-relevant skills that are valuable for my career development.
MC2	The competency-based structure of micro-credentials makes the learning objectives clear and achievable.

Code Micro-Credentials (MC) (Adapted from Varadarajan et al., 2023; Kumar et al., 2022)	
MC3	Earning a digitally verifiable micro-credential certificate increases the value of my learning achievement.
MC4	Micro-credential programmes offered by my university are aligned with national qualification standards (e.g., MQA).
MC5	The modular format of micro-credentials allows me to learn flexibly at my own pace.
<i>1 = Strongly Disagree 2 = Disagree 3 = Neutral 4 = Agree 5 = Strongly Agree</i>	
Code Knowledge Sharing (KS) (Adapted from Sivakumar et al., 2023; Zamiri & Esmaeili, 2024)	
KS1	I actively share my learning experiences and knowledge about micro-credential systems with my peers.
KS2	Peer knowledge sharing about micro-credential platforms helps me understand how to use them more effectively.
KS3	Collaborative digital platforms (e.g., discussion forums, group chats) facilitate effective knowledge exchange in micro-credential learning.
KS4	Sharing knowledge with classmates about micro-credential tools reduces my effort in learning how to use them.
KS5	The exchange of information among students about micro-credential systems improves my overall learning experience.
<i>1 = Strongly Disagree 2 = Disagree 3 = Neutral 4 = Agree 5 = Strongly Agree</i>	
Code Perceived Usefulness (PU) (Adapted from Davis, 1989; Mailizar et al., 2021; Han & Sa, 2021)	
PU1	Using micro-credential learning systems improves my academic and professional performance.
PU2	Micro-credential learning systems enable me to acquire skills more efficiently than traditional learning methods.
PU3	I find micro-credential learning systems useful for achieving my learning and career goals.
PU4	Using micro-credential platforms increases my productivity in skill development.
PU5	Overall, micro-credential learning systems are beneficial for my education and future employability.
<i>1 = Strongly Disagree 2 = Disagree 3 = Neutral 4 = Agree 5 = Strongly Agree</i>	
Code Perceived Ease of Use (PEOU) (Adapted from Davis, 1989; Mailizar et al., 2021; Han & Sa, 2021)	
PEOU1	I find micro-credential learning systems easy to navigate and use.
PEOU2	Learning how to use micro-credential platforms requires minimal effort on my part.
PEOU3	The interface and features of micro-credential systems are clear and understandable.

Code	Perceived Ease of Use (PEOU) (Adapted from Davis, 1989; Mailizar et al., 2021; Han & Sa, 2021)
PEOU4	I can become proficient in using micro-credential learning systems without much difficulty.
PEOU5	Interacting with micro-credential learning platforms is straightforward and flexible.
<i>1 = Strongly Disagree 2 = Disagree 3 = Neutral 4 = Agree 5 = Strongly Agree</i>	
Code	Behavioural Intention (BI) (Adapted from Venkatesh et al., 2003)
BI1	I intend to continue using micro-credential learning systems in the future.
BI2	I plan to enrol in additional micro-credential programmes offered through digital platforms.
BI3	I would recommend micro-credential learning systems to my peers and colleagues.
BI4	I am motivated to increase my use of micro-credential platforms for skill development.
<i>1 = Strongly Disagree 2 = Disagree 3 = Neutral 4 = Agree 5 = Strongly Agree</i>	
Code	Technology Acceptance (TA) (Adapted from Zhao et al., 2024; Mukred et al., 2024)
TA1	I have adopted micro-credential learning systems as part of my regular learning routine.
TA2	I actively use micro-credential platforms to support my academic and professional development.
TA3	I am satisfied with my overall experience of using micro-credential learning systems.
TA4	I consider micro-credential learning systems an important part of my higher education experience.
<i>1 = Strongly Disagree 2 = Disagree 3 = Neutral 4 = Agree 5 = Strongly Agree</i>	

Appendix 2: Sampling Quotas and Inclusion Screening

The inclusion-screening item used to confirm respondent eligibility is Item 4 in Section A of the survey instrument (Appendix 1): “Have you completed at least one micro-credential programme?” Only respondents who selected “Yes” were retained for analysis; responses from those who selected “No” were excluded prior to data cleaning.

Target sampling quotas were set at approximately 12–13 surveys per university-by-discipline stratum ($5 \text{ universities} \times 4 \text{ STEM disciplines} = 20 \text{ strata}$), informed by estimated discipline enrolment shares at each institution, for a total of approximately 247 surveys distributed. This target allocation, combined with an 81.0% usable response rate, yielded the achieved distribution of $N = 200$ respondents reported in Table 2.