

## Revisiting TAM Under Institutional Diversity: Student Acceptance of AI-Based Learning Across Two Southeast Asian Contexts

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**Abstract:** This study aimed to evaluate the measurement and structural models of the Technology Acceptance Model in the context of AI-based learning and to examine whether the hypothesized relationships vary across two university settings with different institutional characteristics. A quantitative survey design was employed involving students from two universities, namely Universiti Kebangsaan Malaysia (UKM) and Universitas Wahid Hasyim (Unwahas). Data were collected through a structured questionnaire covering the core constructs of the Technology Acceptance Model, including perceived ease of use, perceived usefulness, attitude toward use, behavioral intention to use, and actual system use. The data were analyzed using structural equation modeling and multi-group analysis. The analysis was conducted in two stages: first, the evaluation of the measurement model for reliability and validity; then, the assessment of structural relationships and cross-group variation. The measurement model demonstrated acceptable reliability and validity, indicating that the instrument was adequate for subsequent structural testing. In the overall structural model, all five hypothesized relationships were statistically significant, supporting the core sequence proposed by the Technology Acceptance Model. Perceived ease of use positively influenced perceived usefulness and attitude toward use; perceived usefulness positively influenced attitude toward use; attitude toward use positively influenced behavioral intention to use; and behavioral intention to use positively influenced actual system use. Multi-group analysis further revealed that the relationship between perceived ease of use and perceived usefulness was stable across both institutional groups. However, the pathways related to attitude formation and the translation of behavioral intention into actual use showed greater contextual variation. The findings confirm that the Technology Acceptance Model remains a relevant framework for explaining students' adoption of AI-based learning technologies. At the same time, the results indicate that the strength of several acceptance pathways is partly shaped by institutional context. Therefore, AI implementation in higher education should be approached with sensitivity to differences in learning environments and institutional conditions.

**Keywords:** artificial intelligence in education, technology acceptance model, measurement invariance, multi-group SEM, higher education.

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### ■ INTRODUCTION

Artificial Intelligence (AI) has changed the way people learn worldwide, including at colleges and universities. Artificial intelligence (AI) is no longer just a tool for researchers; it has become an important tool for teaching and learning. It now

comprises adaptive learning systems, intelligent guidance systems, and automatic feedback mechanisms (Chen et al., 2022; Lai et al., 2023). A group of real-world studies on the significant effects of AI use in higher education has put students at the center of the research.

This illustrates the strategic use of AI in education to improve the learning experience and cultivate learning analytics that bolster academic success while mitigating the danger of student attrition (Crompton & Burke, 2023; Ocaña-Fernández et al., 2019). This study defines “AI-based learning technologies” as those that directly support learning activities, such as adaptive learning platforms, AI-based learning assistants, automated feedback systems, and generative AI tools. These are not administrative applications (Barragán Moreno & Guzmán Rincón, 2025). Based on this information, colleges and universities need to plan and put into action flexible policies for the systematic growth of digital skills so that they can graduate students who can use and keep improving a digital environment that is supported by AI (Chen et al., 2020; Zhang, 2024).

However, students’ adoption of AI depends not only on access but also on stable perceptions and attitudes that support responsible, sustainable use aligned with learning goals. Because AI use can either enhance self-regulation and learning efficiency or encourage superficial dependence that weakens understanding, integrity, and independent reasoning, it is important to understand the factors shaping students’ acceptance and use of AI-based learning technologies. Simultaneously, the adoption and utilization of AI are likely influenced by contextual conditions beyond individual preferences. The extent to which AI adoption becomes routine learning behavior depends on supporting structures, including infrastructure readiness, instructional design that integrates AI-based tasks, assessment requirements, and peer norms within the learning community. Consequently, research that views AI acceptance as a homogeneous individual phenomenon may overlook systematic differences across educational contexts. This study addresses these concerns by analyzing AI acceptance and use in two different university settings in Southeast Asia.

The concept of Artificial Intelligence in Education (AIEd) can be comprehended through three perspectives. These paradigms are evident in the function of Artificial Intelligence and the collaborative engagement of students working synergistically (Ouyang & Jiao, 2021; Zawacki-Richter et al., 2019). The AI-guided paradigm positions AI as the principal catalyst of the learning process, with learners primarily serving as users of organized instructional services, as evidenced in the initial tradition of intelligent tutoring systems (Almahri et al., 2020). Secondly, the AI-supported paradigm perceives AI as a facilitative instrument that engages in bidirectional interaction with learners, promoting more adaptable and collaborative learning via data-driven analytical processes (Cheng & Lu, 2025; Mustofa et al., 2025). Thirdly, the AI-empowered paradigm underscores AI as a facilitator of human intelligence inside intricate learning systems, prioritizing a human-centered design that is more visible and accountable, allowing learners to direct decision-making in their own educational processes (Gherhes & Obrad, 2018; Hu & Chan, 2025). This perspective aligns with prior literature suggesting that artificial intelligence (AI) can enhance student engagement and tailor the learning experience, contingent upon the congruence between the technology’s design and its implementation context (Popenici & Kerr, 2017; Rienties et al., 2025).

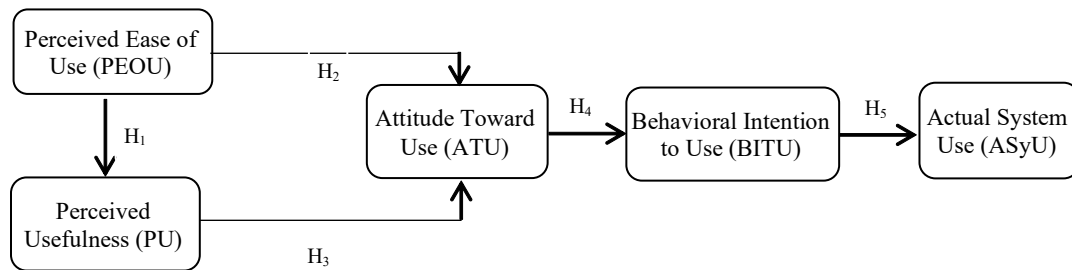
The Technology Acceptance Model (TAM) offers a robust framework for elucidating how university students embrace and utilize AI-based learning tools (Descamps et al., 2025), having been well validated in the realm of educational technology adoption research (Mustofa et al., 2025; Saflor, 2025). The Technology Acceptance Model (TAM) highlights the significance of two fundamental beliefs: Perceived Ease of Use (PEOU) and Perceived Usefulness (PU), in determining Attitude Toward Use (ATU), which in turn affects Behavioral Intention to Use (BI)

and actual usage (Davis, 1989). In this study, TAM is used as a parsimonious baseline for comparing core acceptance pathways across institutional contexts via multi-group SEM, rather than modeling all determinants of AI adoption. Although generative AI involves ethical and agency-related considerations beyond PEOU and PU, adding UTAUT2 constructs or contextual variables would increase model complexity and hinder measurement invariance, reducing the interpretability of cross-group comparisons. Perceived ease of use reflects students' belief that AI technology can be used without excessive effort, which in turn supports the belief that the technology can enhance learning effectiveness and quality (Venkatesh et al., 2003; Venkatesh & Davis, 2000). These perceptions jointly form attitudes toward use that influence behavioral intentions to use the technology on an ongoing basis and ultimately drive actual system use (Cheng & Lu, 2025; Saflor, 2025).

Nevertheless, most research on AI acceptance focuses on a single nation or a specific institutional type, with insufficient theorization of how institutional orientation influences the fundamental Technology Acceptance Model (TAM) mechanism. This is significant because the Technology Acceptance Model (TAM) posits that acceptance is chiefly influenced by utilitarian perceptions of performance enhancement (PU) and effort minimization (PEOU). Conversely, in values-oriented universities, students may assess AI through a more pronounced normative perspective, wherein "usefulness" is construed in terms of educational significance, ethical propriety, and congruence with institutional values. Conversely, research-intensive settings with advanced technology ecosystems may prioritize usability and structural facilitators that help convert intention into habitual practice. Consequently, juxtaposing a research-intensive university (UKM) with a values-oriented

university (Unwahas) serves to address an empirical void while also examining potential boundary conditions of the Technology Acceptance Model in AI-enhanced learning. Cross-group comparisons within SEM should commence with measurement invariance testing to confirm that PEOU, PU, ATU, BI, and actual use are assessed equivalently across groups (Cheng & Lu, 2025; Putnick & Bornstein, 2016; Saihi et al., 2024).

Upon achieving an adequate level of measurement invariance, multi-group SEM can be employed to investigate if the structural correlations across TAM dimensions vary across institutional contexts (Putnick & Bornstein, 2016; Schmitt & Kuljanin, 2008). This study examines two research questions: RQ1: Does the TAM measurement model exhibit appropriate measurement invariance between the two institutional groups? RQ2: Do the structural links among perceived ease of use, perceived usefulness, attitude toward use, behavioral intention to use, and actual system use vary between the two institutional contexts? Drawing from the Technology Acceptance Model and existing literature, five structural hypotheses are posited: H1: perceived ease of use positively influences perceived usefulness; H2: perceived ease of use positively influences attitude toward use; H3: perceived usefulness positively influences attitude toward use; H4: attitude toward use positively influences behavioral intention to use; and H5: behavioral intention to use positively influences actual system use. Furthermore, as this study contrasts a research-intensive with a values-oriented higher education context, it is anticipated that at least one of these structural pathways will differ among the groups. To make the proposed theoretical structure explicit, Figure 1 presents the hypothesized structural model derived from the Technology Acceptance Model and prior literature.



**Figure 1.** Hypothesized structural model of AI-based learning technology acceptance across institutional contexts

## ■ METHOD

### Participants

Participants were undergraduate university students from two institutions in Southeast Asia: UKM and Unwahas. The choice of the two universities was determined by their distinct institutional focuses rather than by their geographical locations alone. UKM was considered a research-intensive institution owing to its official classification as a research university, with research excellence integral to its institutional character. Its robust research-oriented profile aligns with its international ranking success. Concurrently, Unwahas was regarded as a values-centric institution due to its statutes, goals, mission, and academic norms that explicitly underscore the integration of higher education with the principles of Islamic Ahlussunnah wal Jama'ah (Aswaja). This attitude is evident in both formal institutional papers and academic practices, encompassing value-based curriculum elements and Aswaja-related institutional initiatives. Consequently, the categorization in this study is to be interpreted as a juxtaposition of institutional frameworks with varying organizational aims, rather than as a direct comparison of national systems. In this study, these labels are used as shorthand for dominant institutional emphases rather than exclusive institutional identities.

Data were collected using convenience sampling through institutional networks and course-related dissemination channels. The final

analytic sample comprised 350 valid cases, including 223 respondents from Unwahas and 127 respondents from UKM. Although the groups were unequal in size, the adequacy of the smaller group was evaluated statistically. An RMSEA-based SEM power analysis for the hypothesized model ( $df = 125$ ,  $\alpha = .05$ ,  $RMSEA = .05$  vs  $.08$ ) indicated power of 0.86 for  $n = 127$ , suggesting that the UKM subsample was adequate for estimating the model and testing the main structural relations.

### Research Design and Procedures

This research employed a comparative cross-sectional survey to investigate students' acceptance and use of AI-driven learning technologies through the lens of the Technology Acceptance Model (TAM). The analysis concentrated on two higher education environments: UKM, a research-intensive institution, and Unwahas, a values-driven university. The study sought to evaluate whether TAM mechanisms function differently across these institutional contexts following the establishment of measurement equivalence among groups. Data were gathered using an online questionnaire distributed via Google Forms. The survey introduction delineated the research objective, specified AI-based learning technologies in the context of educational activities (excluding administrative applications), and assured confidentiality. Participants completed the survey independently and provided their gender and

country of origin; no personally identifiable information was gathered.

Table 1 summarizes the operational definitions, sources of adaptation, indicators, and example items for each construct.

### Instruments

The instrument comprised five TAM constructs: PEOU, PU, ATU, BITU, and ASyU. All items were rated on a five-point Likert scale.

### Data Analysis

Data analysis proceeded in four stages. First, descriptive statistics and within-group

**Table 1.** Summary of the study instrument

| Construct   | Indicator                             | Item Statement   | No Item |
|---|---------------------------------------|--|---------|
| <b>Perceived Ease of Use (PEOU)</b> (Davis, 1989; Rahayu et al., 2017; Rahmawati et al., 2022; Salmi et al., 2023a) | Easy to Use                           | AI is easy for me to use to support learning.                    | 1       |
|   | Easy to Understand                    | I can easily understand how AI works for my assignments.         | 2       |
|   | Helps Achieve Goals                   | AI makes it easier for me to complete course assignments.        | 3       |
| <b>Perceived Usefulness (PU)</b> (Davis, 1989; Rahayu et al., 2017; Rahmawati et al., 2022; Salmi et al., 2023a)    | Speeds Up Work                        | AI helps me complete assignments faster.                         | 4       |
|   | Improves Quality                      | AI improves the quality of my assignment results.                | 5       |
|   | Enhances Creativity                   | AI helps me to be more creative when working on tasks.           | 6       |
|   | Increases Productivity                | AI increases my learning motivation.                             | 7       |
|   | Overall Beneficial                    | Overall, AI is beneficial in my learning process.                | 8       |
| <b>Attitude Towards Using (ATU)</b> (Rahmawati et al., 2022; Sri Sugiarto et al., 2024)                             | Accepts the Use of AI                 | I accept the use of AI implemented by the university.            | 9       |
|   | Rejects the Use of Other Technologies | I am not interested in using any technologies other than AI.     | 10      |
|   | Enjoys Using AI                       | I enjoy using AI to help with my coursework.                     | 11      |
|   | Easy to Enjoy                         | AI features are easy and enjoyable to use.                       | 12      |
| <b>Behavioral Intention to Use (BITU)</b> (Rahayu et al., 2017; Rahmawati et al., 2022)                             | Future Intention to Use               | I plan to continue using AI for self-development.                | 13      |
|   | High Motivation to Use                | I am motivated to use AI in my learning activities.              | 14      |
|   | Sustained Motivation to Use           | I plan to use AI frequently for my personal and academic growth. | 15      |
|   | Consistent Use                        | I will consistently use AI in various situations.                | 16      |
|   | Recommendation to Others              | I will recommend AI to my friends for learning purposes.         | 17      |
| <b>Actual System Use (AsyU)</b> (Fitria, 2021; Rahayu et al., 2017; Rahmawati et al., 2022; Rienties et al., 2024)  | Following Procedures                  | I use AI according to the provided guidelines or procedures.     | 18      |
|   | Honesty in Use                        | I use AI honestly and in accordance with academic ethics.        | 19      |
|   | Duration of Use                       | I use AI according to the recommended time or duration.          | 20      |

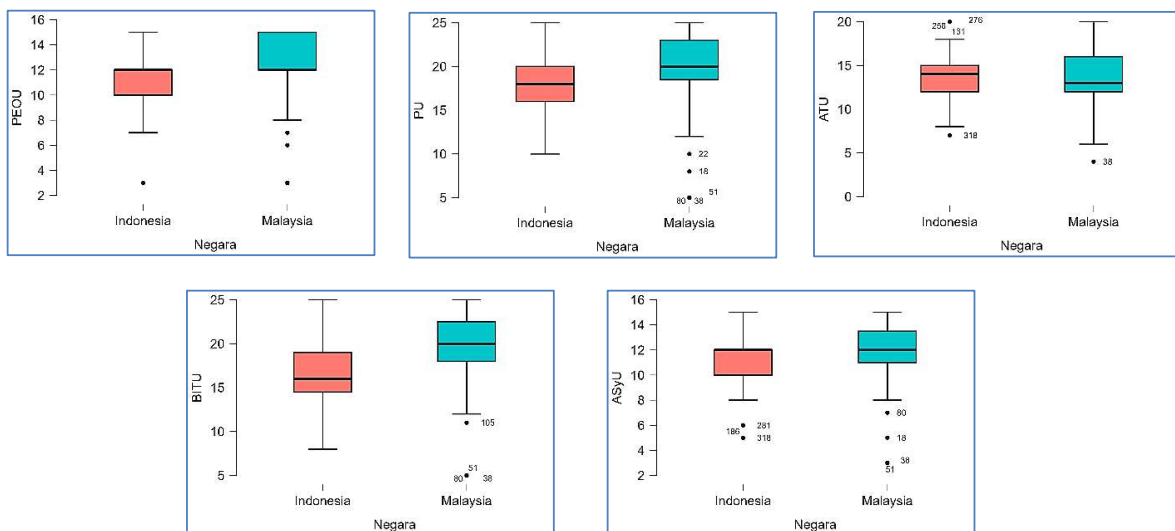
correlations were computed to summarize data characteristics and initial associations among TAM constructs. Second, confirmatory factor analysis (CFA) was conducted to verify the five-factor measurement model (PEOU, PU, ATU, BITU, ASyU) and evaluate measurement quality through factor loadings and fit indices (e.g., CFI, TLI, RMSEA, SRMR). Given the ordinal nature of Likert indicators, estimation used a robust estimator appropriate for ordinal data, and inference did not rely on multivariate normality.

Third, measurement invariance across groups was tested sequentially (configural, metric, and scalar invariance) using changes in incremental fit indices (particularly  $\Delta$ CFI). When full metric invariance was not supported, partial metric invariance was pursued by freeing only a limited number of non-invariant factor loadings, allowing cautious cross-group comparisons of structural relations while avoiding unsupported comparisons of latent means. Fourth, multi-group SEM was used to test group differences in TAM structural

paths by comparing an unconstrained structural model with a constrained model imposing equality on key paths. Robust chi-square difference testing and changes in model fit were used to evaluate whether path coefficients differed significantly between groups, and standardized estimates with significance tests were reported.

## ■ RESULT AND DISCUSSION

Initially, descriptive statistics and correlations are provided to elucidate the status of each construct and the intensity of bivariate relationships among the TAM constructs. Elevated ratings signify more favorable perceptions. Theoretical ranges are delineated as follows: PEOU 3–15; PU 5–25; ATU 4–20; BITU 5–25; ASyU 3–15. Min/Max denotes the recorded values. Following these findings, an assessment of the measurement model was conducted to verify that the connections examined in subsequent analyses accurately represent the constructs assessed with sufficient quality.



**Figure 2.** Boxplots of TAM scores in unwahas and UKM (PEOU, PU, ATU, BITU, ASyU)

The descriptive figure provides an initial indication of inter-construct patterns that align with TAM expectations. Mean differences observed scores across groups are reported without

substantive cross-national interpretation, given that scalar invariance was not established. Accordingly, the inferential focus of this study is directed toward comparing structural relationships

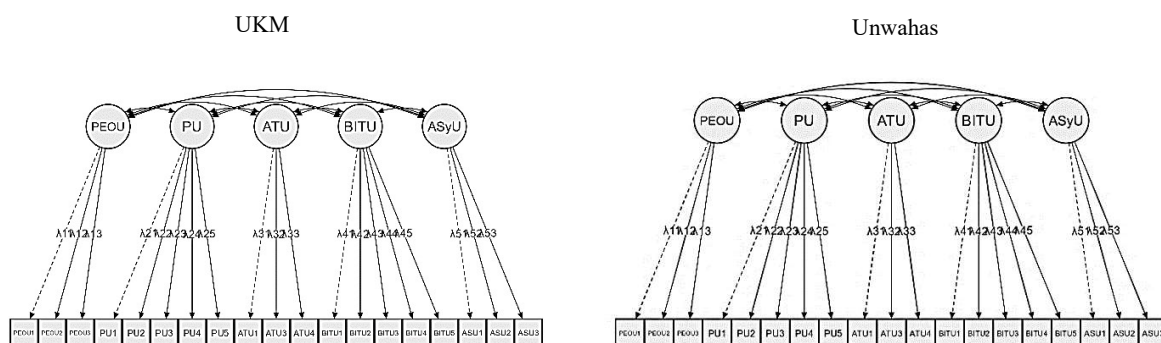
(paths) using multi-group SEM. Observed means were higher in UKM for PEOU ( $M=12.44$ ;  $SD=2.47$ ), PU ( $M=19.97$ ;  $SD=4.18$ ), BITU ( $M=19.69$ ;  $SD=4.08$ ), and ASyU ( $M=12.12$ ;  $SD=2.27$ ) than in Unwahas (respectively: PEOU  $M=11.49$ ;  $SD=1.89$ ; PU  $M=17.93$ ;  $SD=3.14$ ; BITU  $M=16.48$ ;  $SD=3.30$ ; ASyU  $M=11.38$ ;  $SD=1.72$ ), whereas ATU was broadly comparable (Unwahas  $M=13.53$ ;  $SD=2.06$ ; UKM  $M=13.42$ ;  $SD=3.09$ ).

Inter-construct correlations within each group were generally positive, with the strongest associations observed for PEOU–PU and PU–BITU. These results support the anticipated bivariate pattern; however, causal interpretations cannot be drawn from correlational analyses (Saihi et al., 2024). Notably, correlations involving ASyU were more moderate in Unwahas (e.g., PEOU–ASyU  $r=0.299$ ; PU–ASyU  $r=0.334$ ) but substantially higher in UKM (PEOU–ASyU  $r=0.757$ ; PU–ASyU  $r=0.720$ ; BITU–ASyU  $r=0.753$ ), suggesting stronger bivariate links between perceptions and intentions and actual use in the UKM sample.

CFA was conducted to verify the TAM measurement model comprising five latent constructs, namely PEOU, PU, ATU, BITU, and

ASyU, prior to cross-group analyses. The analysis was performed using data from the two institutional groups ( $N=350$ ; Unwahas  $n=223$ ; UKM  $n=127$ ). In the initial model, ATU2 showed very low factor loadings across both groups and was therefore removed from the measurement model. The CFA was subsequently re-estimated using the revised set of indicators. The revised model produced a significant chi-square value,  $\chi^2(284) = 687.084$ ,  $p < .001$ , and showed acceptable but not optimal fit according to the additional fit indices (CFI = 0.908, TLI = 0.889, RMSEA = 0.090, SRMR = 0.058). Overall, most indicators loaded adequately on their intended constructs, supporting the revised model for subsequent reliability, validity, and measurement invariance analyses. The CFA diagram illustrates a five-factor structure comprising diverse yet positively linked constructs, particularly among conceptually related constructs such as PEOU and PU. Overall, the revised model was retained for subsequent reliability, validity, and invariance testing (Fig. 3).

Furthermore, the parameter estimation results indicate that item ATU2 within the Attitude Towards Use construct has very low factor



**Figure 3.** CFA measurement model for TAM with standardized factor loadings

**Table 2.** Evidence for the removal of the problematic ATU item

| Item | UKM $\lambda$ | Unwahas $\lambda$ | Decision |
|------|---------------|-------------------|----------|
| ATU2 | 0.173         | 0.154             | Removed  |

loadings in both groups (UKM  $\bar{\epsilon}$  = 0.173; Unwahas  $\bar{\epsilon}$  = 0.154). These findings suggest that this item does not contribute significantly to reflecting the ATU construct. In light of this, item ATU2 was removed from the measurement model, and the CFA, measurement invariance, and multi-group SEM analyses were re-estimated using the revised model.

**Table 3.** Factor loadings for the revised measurement model across groups

| <i>Factor loadings</i> |        |           |          |            |         |        | 95% Confidence Interval |       |
|------------------------|--------|-----------|----------|------------|---------|--------|-------------------------|-------|
| Group                  | Factor | Indicator | Estimate | Std. Error | z-value | p      | Lower                   | Upper |
| UKM                    | PEOU   | PEOU1     | 1.000    | 0.000      |         |        | 1.000                   | 1.000 |
|                        |        | PEOU2     | 1.086    | 0.083      | 13.013  | < .001 | 0.923                   | 1.250 |
|                        |        | PEOU3     | 1.154    | 0.086      | 13.428  | < .001 | 0.986                   | 1.323 |
|                        | PU     | PU1       | 1.000    | 0.000      |         |        | 1.000                   | 1.000 |
|                        |        | PU2       | 1.095    | 0.101      | 10.794  | < .001 | 0.896                   | 1.293 |
|                        |        | PU3       | 1.026    | 0.085      | 12.025  | < .001 | 0.859                   | 1.193 |
|                        |        | PU4       | 1.104    | 0.093      | 11.881  | < .001 | 0.922                   | 1.286 |
|                        |        | PU5       | 0.988    | 0.085      | 11.589  | < .001 | 0.821                   | 1.155 |
|                        | ATU    | ATU1      | 1.000    | 0.000      |         |        | 1.000                   | 1.000 |
|                        |        | ATU3      | 0.238    | 0.138      | 1.727   | .084   | -0.032                  | 0.508 |
|                        |        | ATU4      | 0.900    | 0.074      | 12.150  | < .001 | 0.754                   | 1.045 |
|                        | BITU   | BITU1     | 1.000    | 0.000      |         |        | 1.000                   | 1.000 |
|                        |        | BITU2     | 1.072    | 0.087      | 12.276  | < .001 | 0.901                   | 1.243 |
|                        |        | BITU3     | 1.079    | 0.092      | 11.775  | < .001 | 0.899                   | 1.258 |
|                        |        | BITU4     | 1.186    | 0.104      | 11.368  | < .001 | 0.982                   | 1.391 |
|                        |        | BITU5     | 1.133    | 0.101      | 11.270  | < .001 | 0.936                   | 1.330 |
|                        | ASyU   | ASyU1     | 1.000    | 0.000      |         |        | 1.000                   | 1.000 |
|                        |        | ASyU2     | 0.895    | 0.080      | 11.145  | < .001 | 0.737                   | 1.052 |
| ASyU3                  |        | 0.895     | 0.094    | 9.545      | < .001  | 0.711  | 1.079                   |       |
| Unwahas                | PEOU   | PEOU1     | 1.000    | 0.000      |         |        | 1.000                   | 1.000 |
|                        |        | PEOU2     | 1.136    | 0.099      | 11.519  | < .001 | 0.942                   | 1.329 |
|                        |        | PEOU3     | 1.098    | 0.097      | 11.331  | < .001 | 0.908                   | 1.288 |
|                        | PU     | PU1       | 1.000    | 0.000      |         |        | 1.000                   | 1.000 |
|                        |        | PU2       | 1.477    | 0.159      | 9.271   | < .001 | 1.165                   | 1.790 |
|                        |        | PU3       | 1.065    | 0.140      | 7.591   | < .001 | 0.790                   | 1.340 |
|                        |        | PU4       | 1.264    | 0.162      | 7.801   | < .001 | 0.947                   | 1.582 |
|                        |        | PU5       | 1.087    | 0.125      | 8.717   | < .001 | 0.842                   | 1.331 |
|                        | ATU    | ATU1      | 1.000    | 0.000      |         |        | 1.000                   | 1.000 |
|                        |        | ATU3      | 1.090    | 0.116      | 9.390   | < .001 | 0.862                   | 1.317 |
|                        |        | ATU4      | 1.073    | 0.116      | 9.261   | < .001 | 0.846                   | 1.300 |
|                        | BITU   | BITU1     | 1.000    | 0.000      |         |        | 1.000                   | 1.000 |
|                        |        | BITU2     | 0.834    | 0.078      | 10.682  | < .001 | 0.681                   | 0.987 |
|                        |        | BITU3     | 0.985    | 0.084      | 11.772  | < .001 | 0.821                   | 1.149 |
|                        |        | BITU4     | 0.977    | 0.093      | 10.502  | < .001 | 0.795                   | 1.159 |
|                        |        | BITU5     | 0.740    | 0.078      | 9.479   | < .001 | 0.587                   | 0.893 |
|                        | ASyU   | ASyU1     | 1.000    | 0.000      |         |        | 1.000                   | 1.000 |
|                        |        | ASyU2     | 1.295    | 0.119      | 10.927  | < .001 | 1.063                   | 1.527 |
| ASyU3                  |        | 1.019     | 0.105    | 9.708      | < .001  | 0.813  | 1.225                   |       |

Following the analysis of component loadings, construct-level reliability and convergent validity were assessed to ascertain whether each latent variable was measured with sufficient consistency across groups. Table 4 displays Cronbach's alpha, omega, composite reliability, and AVE for the UKM and Unwahas samples. Generally, most constructs exhibited satisfactory

measurement quality; however, ATU in the UKM group appeared comparatively weak, and PU in the Unwahas group showed questionable convergent validity. The results suggest that the altered instrument was largely sufficient for future measurement invariance and structural model studies, but caution is advised in interpreting the weaker constructs.

**Table 4.** Reliability and convergent validity of the revised measurement model across groups

| Group   | Construct | McDonald's $\omega$ | Cronbach's $\alpha$ | AVE   | Interpretation   |
|---------|-----------|---------------------|---------------------|-------|--|
| UKM     | PEOU      | 0.909               | 0.912               | 0.776 | Good reliability; acceptable convergent validity       |
|         | PU        | 0.922               | 0.919               | 0.698 | Good reliability; acceptable convergent validity       |
|         | ATU       | 0.574               | 0.578               | 0.381 | Low reliability; weak convergent validity              |
|         | BITU      | 0.924               | 0.922               | 0.705 | Good reliability; acceptable convergent validity       |
|         | ASyU      | 0.841               | 0.838               | 0.636 | Good reliability; acceptable convergent validity       |
| Unwahas | PEOU      | 0.818               | 0.817               | 0.600 | Acceptable reliability; acceptable convergent validity |
|         | PU        | 0.809               | 0.802               | 0.461 | Acceptable reliability; marginal convergent validity   |
|         | ATU       | 0.755               | 0.745               | 0.500 | Acceptable reliability; acceptable convergent validity |
|         | BITU      | 0.853               | 0.849               | 0.539 | Good reliability; acceptable convergent validity       |
|         | ASyU      | 0.819               | 0.809               | 0.601 | Acceptable reliability; acceptable convergent validity |

The results for reliability and convergent validity indicate that the amended instrument had generally acceptable measurement properties across most TAM constructs. The majority of AVE values either met or nearly approximated the required threshold, signifying sufficient convergent validity for most constructs. Nonetheless, the ATU construct within the UKM group exhibited weak convergent validity (AVE = 0.381), while PU in the Unwahas group

displayed moderate convergent validity (AVE = 0.461). Regarding internal consistency, the majority of constructs exhibited adequate McDonald's omega and Cronbach's alpha values, although the ATU in the UKM group fell short of the suggested threshold ( $\omega = 0.574$ ;  $\alpha = 0.578$ ). Collectively, these findings endorse the use of the amended instrument for further analyses, while advising prudence in interpreting outcomes pertaining to ATU in the UKM group.

**Table 5.** Goodness-of-Fit indices for measurement invariance models

| Model      | CFI   | TLI   | RMSEA | SRMR  | $\chi^2$ | df  | p      |
|------------|-------|-------|-------|-------|----------|-----|--------|
| Configural | 0.908 | 0.889 | 0.090 | 0.056 | 687.084  | 284 | < .001 |
| Metric     | 0.900 | 0.885 | 0.092 | 0.083 | 736.060  | 298 | < .001 |
| Scalar     | 0.875 | 0.863 | 0.100 | 0.104 | 859.854  | 312 | < .001 |

Measurement invariance testing was conducted in three stages: configural, metric, and scalar. The configural model demonstrated adequate fit (CFI = 0.908; TLI = 0.889; RMSEA = 0.090; SRMR = 0.056), indicating that the same factor structure applies to both groups. At the metric stage, the model still showed an acceptable fit (CFI = 0.900; TLI = 0.885; RMSEA = 0.092; SRMR = 0.083), with a 0.008 decrease in CFI relative to the configural model. This data indicates that metric invariance is acceptable. However, at the scalar stage, the

model fit deteriorated further (CFI = 0.875; TLI = 0.863; RMSEA = 0.100; SRMR = 0.104), with a 0.025 decrease in CFI relative to the metric model, indicating that scalar invariance was not met. Consequently, comparisons between groups are limited to relationships between constructs and are not extended to comparisons of latent means. In the overall SEM model, all five hypothesized TAM paths statistically significant. However, subsequent multi-group analysis showed that the strength and significance of several paths varied across institutional contexts.

**Table 6.** Structural path estimates in the overall SEM model

| Hypothesis | Path        | Estimate | p      | Decision  |
|------------|-------------|----------|--------|-----------|
| H1         | PEOU → PU   | 0.918    | < .001 | Supported |
| H2         | PEOU → ATU  | 0.299    | .015   | Supported |
| H3         | PU → ATU    | 0.665    | < .001 | Supported |
| H4         | ATU → BITU  | 1.082    | < .001 | Supported |
| H5         | BITU → ASyU | 0.574    | < .001 | Supported |

Next, differences in TAM structural paths were examined by comparing an unconstrained model with a constrained model. The robust difference test indicated a significant discrepancy between models  $\Delta\chi^2 = 27.069$ ;  $\Delta df = 5$ ;  $p < .001$  suggesting that not all TAM paths are equivalent between Unwahas and UKM. In UKM, the PEOU'!PU path was very strong and significant ( $\beta = 0.937$ ), and BITU'!ASyU was also significant and strong ( $\beta = 0.896$ ) whereas PU'!ATU was not significant. The PEOU'!ATU path was significant ( $\beta = 0.684$ ) and ATU'!BITU was not significant at  $\alpha = 0.05$  ( $\beta = 0.978$ ;  $p$

$= .054$ ); therefore, evidence for this path in the UKM group was weak and was not treated as a primary basis for the main conclusions. For Unwahas,  $p = 0.050$  was exactly at the conventional significance threshold ( $\beta = 0.789$ ;  $p = .050$ ), and the interpretation was therefore made conservatively. In Unwahas, PEOU'!PU remained significant ( $\beta = 0.864$ ), but attitude formation was more strongly driven by PU (PU → ATU significant;  $\beta = 0.640$ ) than by PEOU (PEOU → ATU not significant at the 5% level), and the BITU → ASyU effect remained significant but was weaker ( $\beta = 0.449$ ).

**Table 7.** Multi-Group SEM Results: TAM path coefficients by group

| Path        | UKM $\beta$ (std) | p      | Unwahas $\beta$ (std) | p      |
|-------------|-------------------|--------|-----------------------|--------|
| PEOU → PU   | 0.937             | < .001 | 0.864                 | < .001 |
| PEOU → ATU  | 0.684             | 0.040  | 0.365                 | 0.067  |
| PU → ATU    | 0.253             | 0.275  | 0.640                 | 0.010  |
| ATU → BITU  | 0.978             | 0.054  | 0.789                 | 0.050  |
| BITU → ASyU | 0.896             | 0.013  | 0.449                 | 0.032  |

### Measurement and Structural Model Validity

The results offer sufficient evidence for the validity of the modified measurement and

structural models employed in this research. The confirmatory factor analysis initially indicated that one indicator within the ATU construct, specifically

ATU2, performed subpar in both institutional groups, as evidenced by relatively low factor loadings in UKM and Unwahas. This suggests that the item failed to serve as a significant indicator of attitudes toward AI use in both contexts, thereby undermining the coherence of the original measurement model. Following the elimination of this problematic element, the amended five-factor TAM model was preserved and exhibited a satisfactory overall fit. Although the fit indices did not indicate an optimal model, the amalgamation of CFI, TLI, RMSEA, and SRMR indicates that the modified structure was adequately justified for subsequent validity and structural investigations. The proposed dimensions of perceived ease of use, perceived usefulness, attitude toward use, behavioral intention to use, and actual system use were empirically distinct and sufficiently represented in the revised model.

Additional evidence for the modified measurement model is evident in the factor loadings, reliability, and convergent validity results. The majority of indicators were appropriately aligned with their designated constructs, indicating that the observed items effectively represented the latent variables they were intended to measure. At the construct level, most omega and Cronbach's alpha coefficients attained acceptable or commendable levels, and the majority of AVE values met or almost neared the suggested threshold. This trend suggests that the modified instrument had adequate internal consistency and convergent validity in both groups. Nonetheless, the findings indicate that the quality of measurement was not uniformly robust across all constructs. The ATU construct in the UKM sample showed relative weakness, as evidenced by low reliability and inadequate convergent validity. Furthermore, the Perceived Usefulness (PU) construct in the Unwahas group showed relatively minimal convergent validity. The results do not undermine the model's applicability; nonetheless, they indicate that interpretations

related to these constructs should be approached with greater caution than other TAM aspects, particularly because the low reliability and inadequate convergent validity suggest potential limitations in the accuracy of the findings. The modified instrument was functional and analytically viable; however, not all components of the model exhibited equivalent psychometric robustness, particularly in reliability and validity across groups.

The cross-group validity of the measurement model was additionally assessed by measurement invariance testing. The configural model demonstrated an adequate match, suggesting that the same overarching factor structure was validated in both UKM and Unwahas. This is a significant baseline finding, as it indicates that students from both institutions perceived the TAM dimensions in largely the same manner. At the metric level, the reduction in model fit remained within an acceptable range, reinforcing the finding that the indicators corresponded to their latent constructs in a sufficiently analogous manner across groups. This outcome is methodologically significant as it validates the comparison of structural relationships among the TAM constructs across the two institutional contexts. Nonetheless, scalar invariance was not attained, evidenced by the significant decline in fit in the scalar stage. This indicates that while the construct structure and loading patterns were generally similar, the item intercepts were not sufficiently equal to provide meaningful comparisons of latent means. Consequently, the study can validly analyze the relationships of TAM variables between groups. However, it should refrain from asserting that one institutional group is unequivocally superior or inferior to another at the level of latent constructs.

Collectively, these data suggest that the structural model was adequately anchored in an acceptable measuring framework. This point is significant because structural interpretation is

believable only when the foundational measurement model is sufficiently valid. The improved CFA results, acceptable reliability, and convergent validity evidence, along with support for configural and metric invariance, collectively establish a sufficient foundation for advancing to SEM and multi-group structural analysis. The deficiencies in model fit and the subpar psychometric performance of chosen constructs suggest that the model should be regarded as sufficient rather than impeccable. The structural model in this study is sufficiently robust for analyzing the relationships among TAM variables across different institutional contexts. However, it requires caution with constructs of lower measurement quality and with interpretations that extend beyond structural path comparisons. This renders the ensuing hypothesis testing analytically justifiable, but solely within the confines of comparing relational processes rather than latent mean discrepancies between UKM and Unwahas.

### **Hypothesis Testing Across Institutional Contexts**

The results of hypothesis testing usually corroborate the fundamental principles of the Technology Acceptance Model, while also indicating that the strength of certain correlations depends on the institutional context. In the overall SEM model, all five hypothesized paths were statistically significant, indicating that the proposed TAM sequence remained broadly applicable to AI-based learning adoption in this study. Perceived ease of use positively influenced perceived usefulness and attitude toward use; perceived usefulness positively influenced attitude toward use; attitude toward use positively influenced behavioral intention to use; and behavioral intention positively influenced actual system use. Collectively, our data indicate that students' acceptance of AI-based learning aids adheres to the traditional Technology Acceptance

Model (TAM) trajectory, progressing from cognitive assumptions to attitudinal development, subsequently to behavioral intention, and ultimately to reported usage (Chen et al., 2022; Ouyang & Jiao, 2021). Thus, at the aggregate level, H1 through H5 were supported.

Of the five hypotheses, H1 garnered the most robust and consistent endorsement (Davis, 1989). The relationship between PEOU and PU was substantial and statistically significant in the entire model, maintaining robustness across both institutional groups. This discovery substantiates a fundamental proposition of the Technology Acceptance Model, specifically that technologies regarded as more user-friendly are more likely to be deemed valuable (Kotlyar & Krasman, 2025; Mustofa et al., 2025). In the realm of AI-driven education, this finding is significantly pertinent, since students are unlikely to regard AI tools as educationally beneficial if they are perceived as laborious, perplexing, or challenging to use (Crompton & Burke, 2023; Habibi et al., 2023; Ocaña-Fernández et al., 2019). The consistency of this trajectory between UKM and Unwahas indicates that usability serves as a common basis for AI acceptance, irrespective of institutional variations. In essence, despite variations in institutional cultures, the belief that AI can be used with minimal effort consistently serves as a reliable indicator of perceived advantage.

The findings for H2 and H3, however, suggest that the development of attitude toward usage is more context-dependent (Roe et al., 2025; Venkatesh et al., 2003). In the comprehensive model, both perceived ease of use and perceived usefulness strongly influenced the attitude toward usage, aligning with the TAM (Anita et al., 2025). However, the multi-group findings indicate that these two attitudinal routes do not function with equivalent significance in the two institutions. Within the UKM group, perceived ease of use appears to exert a relatively

greater influence on attitude, suggesting that students in this environment may be more receptive to the practical efficiency of using AI tools (Habibi et al., 2023). Conversely, in the Unwahas group, perceived usefulness emerges as the predominant factor in attitude formation, suggesting that students' attitudes are more closely linked to the perception of AI as actually advantageous for learning (Gherhes & Obrad, 2018; Qiu et al., 2022). This distinction is theoretically significant because it implies that attitudes toward AI use are not formed through a single universal method. The equilibrium between usability and utility may fluctuate based on the institutional context (Saihi et al., 2024). Consequently, although H2 and H3 are generally endorsed, their significance varies by context.

This contextual variance is a significant finding of the study, as it extends the Technology Acceptance Model beyond mere validation. Much TAM research in educational technology considers the attitudinal process to be predominantly constant across contexts, with perceived ease of use and perceived usefulness influencing outcomes in rather predictable manners (Fernández-Ferrer et al., 2025; Hu & Chan, 2025; Kotlyar & Krasman, 2025). In contrast, the current data indicate that AI acceptability in higher education may be influenced by varying priorities across several institutional contexts. In a research-intensive environment like UKM, usability may be more significant since students are inclined to utilize AI as a productivity-enhancing instrument, where efficiency and little resistance are particularly prominent (Almahri et al., 2020; Gherhes & Obrad, 2018). In a values-driven environment like Unwahas, utility may be of more significance, as acceptability is likely contingent upon the technology's perceived educational value and its alignment with substantial learning outcomes (Descamps et al., 2025). This interpretation must be conveyed with caution, as contextual factors were not directly

assessed. The observed pattern aligns with the notion that institutional context may serve as a boundary constraint in the functioning of TAM pathways for AI-based learning.

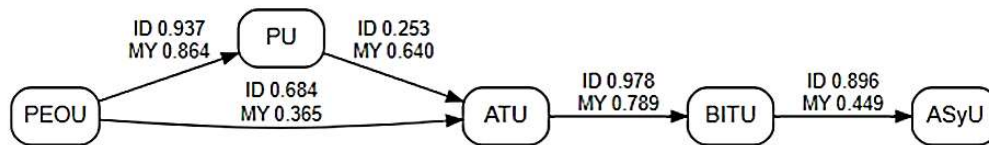
Hypothesis 4, which posits that it positively affects behavioral intention to use, was also corroborated in the entire model. This outcome is theoretically anticipated, as the Technology Acceptance Model posits that positive sentiments regarding a technology correlate with an increased propensity to persist in its use (Hu & Chan, 2025; Lai et al., 2023). The multi-group findings demonstrate that this pathway remained positive in both groups, indicating that the relationship between attitude and intention is generally consistent across institutional contexts. Nonetheless, the evidence supporting this trajectory at the group level is less compelling than that for H1; it should not be exaggerated. A more tenable view is that students with more positive attitudes toward AI-based learning tools are likewise likely to express greater intent to use them; however, the strength of this correlation may vary across contexts. Consequently, H4 may be considered supported, albeit with more circumspection than the more substantial PEOU → PU connection.

H5, regarding the correlation between behavioral intention to utilize and actual system usage, was similarly validated; however, the multi-group analysis indicated a significant contextual disparity. In both cohorts, a heightened behavioral intention was associated with increased reported utilization of AI-driven educational technology (Khotimah, 2026). This trajectory was more evident in the UKM group compared to the Unwahas group. This outcome indicates that intention is more effectively translated into actual use in a research-intensive environment (Fahmy, 2024; Salmi et al., 2023b). A reasonable view is that contextual supports in UKM may more effectively facilitate students in converting willingness into habitual practice (Rienties et al.,

2025). Such supports may encompass enhanced digital infrastructure, increased engagement with technology-mediated academic endeavors, or more lenient rules regarding AI-assisted learning (Rienties et al., 2025; Sri Sugiarto et al., 2024). These explanations are inferential rather than empirically validated; they should not be presented as causal assertions (Pardamean et al., 2022; Salmi et al., 2023a). Nevertheless, the pattern is significant as it suggests that intention alone is not uniformly actionable across all institutional contexts. Consequently, H5 is endorsed; its practical efficacy is more pronounced in UKM than in Unwahas.

The hypothesis-testing results indicate that the TAM framework is effective in explaining students' acceptance of AI-based learning technology, albeit not uniformly across contexts. The comprehensive model validates the

anticipated sequence of links between perceived ease of use, perceived utility, attitude, intention, and actual usage. The multi-group data indicate that the attitudinal and behavioral segments of the model are influenced by the institutional context. The most consistent conclusion is that perceived ease of use plays a pivotal role in influencing perceived usefulness. In contrast, the routes to attitude and the transformation of intention into actual usage differ markedly between the two colleges. This study's contribution is twofold: it confirms hypotheses H1 through H5 at an aggregate level and demonstrates that the functioning of these assumptions is partially influenced by the institutional setting. The TAM framework is analytically beneficial, suggesting that implementation plans for AI in higher education must recognize that acceptance pathways vary across distinct university contexts.



**Figure 4.** Multi-group SEM of the TAM structural model: standardized path coefficients by group (ID = Unwahas; MY = UKM)

This study has several limitations. First, the cross-sectional design limits causal inference; therefore, the direction of relationships is interpreted as associative patterns consistent with TAM. Second, self-report data may introduce common method bias. Third, the failure to establish scalar invariance limits cross-group comparisons of latent means, thereby focusing the comparative interpretation on differences in structural paths. Future research could employ longitudinal designs or experience sampling methods to capture the dynamics of intention and actual use, and extend the model by incorporating contextual variables such as institutional support, subjective norms, AI literacy, and perceptions of risk and ethics.

## CONCLUSION

This study suggests that the Technology Acceptance Model is an effective paradigm for elucidating students' acceptance of AI-based learning technology in both university contexts. At the aggregate level, all proposed linkages were validated, demonstrating that students' acceptance often progresses from perceived ease of use and perceived utility to attitude, behavioral intention, and actual usage. Nonetheless, the multi-group results indicate that the relative potency of various paths differs among institutional contexts. Specifically, reported ease of use reliably predicts perceived usefulness across several populations, whereas the attitudinal and behavioral pathways are more contingent on

context. These findings indicate that the deployment of AI in higher education should not be perceived as functioning through a completely consistent mechanism. Consequently, the study not only reinforces the Technology Acceptance Model (TAM) within the realm of AI-driven learning but also illustrates that the institutional framework somewhat influences the formation of acceptance and its translation into practical usage. This necessitates that colleges formulate AI deployment strategies tailored to their specific learning environments, student expectations, and institutional resources.

#### ■ DECLARATION OF GENERATIVE AI USAGE IN THE WRITING PROCESS

Generative AI was used in the writing process to support ideation, improve clarity and coherence, and assist with language editing of selected passages. The tool used was ChatGPT (version 5.2). Generative AI was not used to generate or modify empirical data, statistical analyses, results, or scientific conclusions. All statistical analyses were conducted by the authors using JASP and RStudio, and all AI-assisted text was critically reviewed, substantially edited, and validated by the authors. The authors take full responsibility for the final content of the manuscript, including the accuracy of interpretations and citations.

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