

# Extending UTAUT2 to Explain Artificial Intelligence Adoption Among University Students in Indonesian Islamic Higher Education: An Empirical SEM-PLS Study

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## ARTICLE INFO

### **Keywords:**

Artificial Intelligence; higher education; UTAUT2; behavioral intention; SEM-PLS; technology adoption

### **Article history:**

Received 2025-10-27

Revised 2026-05-16

Accepted 2026-07-15

## ABSTRACT

Empirical evidence on AI adoption in Islamic higher education institutions within emerging economies remains limited, as prior studies have predominantly focused on universities in developed countries and have rarely examined the applicability of the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) in this unique educational context. Addressing this gap, this study extends the UTAUT2 framework to examine the determinants of AI adoption among students at Islamic universities in Pekanbaru, Indonesia. A quantitative approach was employed using survey data collected from 200 students through probability sampling and analyzed with Structural Equation Modeling–Partial Least Squares (SEM-PLS). The results reveal that Performance Expectancy, Facilitating Conditions, Hedonic Motivation, and Habit significantly influence Behavioral Intention, whereas Effort Expectancy, Social Influence, and Price Value do not. Furthermore, Behavioral Intention has a strong positive effect on Use Behavior. The structural model demonstrates substantial explanatory power, with an  $R^2$  of 0.721 for Behavioral Intention and 0.428 for Use Behavior, indicating that the proposed model effectively explains students' AI adoption behavior. This study contributes theoretically by validating and extending UTAUT2 in the underexplored context of Islamic higher education in an emerging economy, highlighting the dominant roles of perceived usefulness, intrinsic motivation, and habitual technology use. Practically, the findings provide evidence-based guidance for university leaders and policymakers to develop AI-supported learning environments through improved digital infrastructure, student engagement strategies, and sustainable AI integration in higher education.

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## INTRODUCTION

The rapid advancement of Artificial Intelligence (AI) has fundamentally transformed higher education by enabling personalized learning, adaptive systems, predictive analytics, and automated academic support tools (Deng et al., 2025; Kelly et al., 2023; Yusiana, 2025). AI technologies are increasingly viewed as strategic instruments for improving learning effectiveness, enhancing student engagement, and supporting data-driven educational decision-making (Granić & Marangunić, 2019; Purwati et al., 2025). AI-based educational tools, including intelligent tutoring systems, virtual assistants, and automated assessment systems, have demonstrated considerable potential in improving learning experiences and optimizing teaching processes. Furthermore, recent studies indicate that AI adoption not only creates opportunities for efficiency and innovation but also introduces challenges related to trust, technological readiness, ethical concerns, and user adaptation (Uren & Edwards, 2023). Therefore, the successful implementation of AI in education depends not only on technological availability but also on users' willingness to adopt and continuously use these systems.

In Indonesia, higher education institutions have increasingly integrated digital technologies into teaching and learning processes. Various educational technology initiatives have contributed to the development of digital learning ecosystems, particularly through Learning Management Systems (LMS), e-learning platforms, and online collaborative tools. However, while digital transformation in education has progressed substantially, the implementation of AI. Recent studies in educational technology also suggest that although students demonstrate positive perceptions toward digital learning environments, institutions continue to encounter barriers associated with technological infrastructure, digital literacy, and readiness for emerging technologies. Existing challenges also involve concerns regarding transparency, ethical implications, and trust in AI systems (Aprilianto et al., 2025; Asnefi et al., 2026; Musa et al., 2022; Sharma & Singh, 2024). These challenges become even more pronounced in Indonesian Islamic universities, where AI implementation must align not only with technological readiness but also with institutional missions emphasizing Islamic values, academic integrity, ethical responsibility, and character-based education. In addition, the increasing adoption of AI in Indonesian higher education is taking place within a regulatory environment that promotes digital transformation while simultaneously requiring responsible, transparent, and ethical AI use. Consequently, students' acceptance of AI may be influenced not only by technological considerations but also by value-based, ethical, and institutional factors that have received limited scholarly attention.

Previous studies on technology adoption in educational settings have predominantly focused on conventional digital learning technologies such as LMS, online learning platforms, and e-learning systems (Jannah et al., 2026; Mozie et al., 2025; Raffaghelli et al., 2022). However, empirical investigations specifically addressing AI-based educational technologies remain limited. This constitutes an empirical gap because AI systems differ significantly from traditional digital systems due to their adaptive intelligence, autonomous decision-making, and personalized interaction capabilities (Acosta-Enriquez et al., 2024; Ali et al., 2026; Ballesteros et al., 2024). Moreover, previous findings have reported inconsistent results regarding the determinants of AI adoption behavior. While some studies identified performance expectancy and facilitating conditions as dominant predictors, others emphasized motivational and social factors as more influential determinants. Such inconsistencies indicate that the mechanisms underlying AI adoption behavior are still not fully understood.

A contextual gap also emerges because most studies investigating AI adoption in higher education have been conducted in developed and technologically advanced regions, including Europe, East Asia, and Latin America (Cabero-Almenara et al., 2025; Tian et al., 2024). Although these studies provide valuable insights, differences in technological infrastructure, educational systems, and sociocultural

environments limit the applicability of their findings to developing countries such as Indonesia (Xue et al., 2026; Yuan et al., 2025). The Indonesian higher education context possesses unique characteristics related to digital inequality, varying institutional readiness, and differences in technological accessibility, which may influence students' perceptions and behavioral intentions toward AI usage. More importantly, Islamic universities represent a distinctive educational environment where technology adoption is expected to support educational excellence while remaining consistent with religious values, ethical norms, and institutional governance. These contextual characteristics distinguish Islamic higher education from general universities and warrant separate empirical investigation. Consequently, localized evidence explaining AI acceptance behavior among Indonesian students remains insufficient.

From a methodological perspective, previous studies have frequently concentrated on measuring general digital readiness or technological literacy instead of examining specific behavioral mechanisms influencing AI adoption. Additionally, many studies investigated individual variables independently without comprehensively analyzing the interaction between cognitive, motivational, and habitual dimensions that influence users' behavioral intentions toward AI technologies. This methodological limitation restricts a more holistic understanding of technology acceptance behavior in AI-supported learning environments.

Theoretical limitations are also evident within existing literature. Traditional technology acceptance models such as TAM and UTAUT primarily focus on cognitive and functional aspects of technology use. However, AI-based technologies involve broader dimensions including emotional engagement, habitual usage patterns, and user experiences that may not be sufficiently explained by conventional frameworks alone. Furthermore, these models have rarely been examined within Islamic higher education environments, where technology acceptance may be shaped by institutional culture, ethical considerations, and contextual educational values alongside conventional technological determinants. Consequently, the explanatory power of existing models remains uncertain in this setting. Therefore, a more comprehensive theoretical approach is required to explain the complexity of AI acceptance behavior in educational settings.

To address these gaps, this study adopts the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model proposed by (Venkatesh et al., 2012). The UTAUT2 framework extends the original UTAUT model by incorporating additional constructs such as hedonic motivation, price value, and habit, thereby providing a broader understanding of technology acceptance behavior. The model has been widely applied in studies related to digital technology adoption and AI-supported systems because it integrates cognitive, social, and behavioral dimensions influencing users' intentions and actual technology usage. Nevertheless, its applicability in Indonesian Islamic higher education has not been sufficiently validated. AI adoption in this context involves unique interactions between perceived usefulness, intrinsic motivation, habitual technology use, institutional support, and ethical considerations that extend beyond the assumptions of conventional technology adoption studies. Accordingly, applying and validating UTAUT2 within this setting provides an opportunity to examine the robustness of the model while enriching the theoretical understanding of AI acceptance in value-oriented higher education institutions.

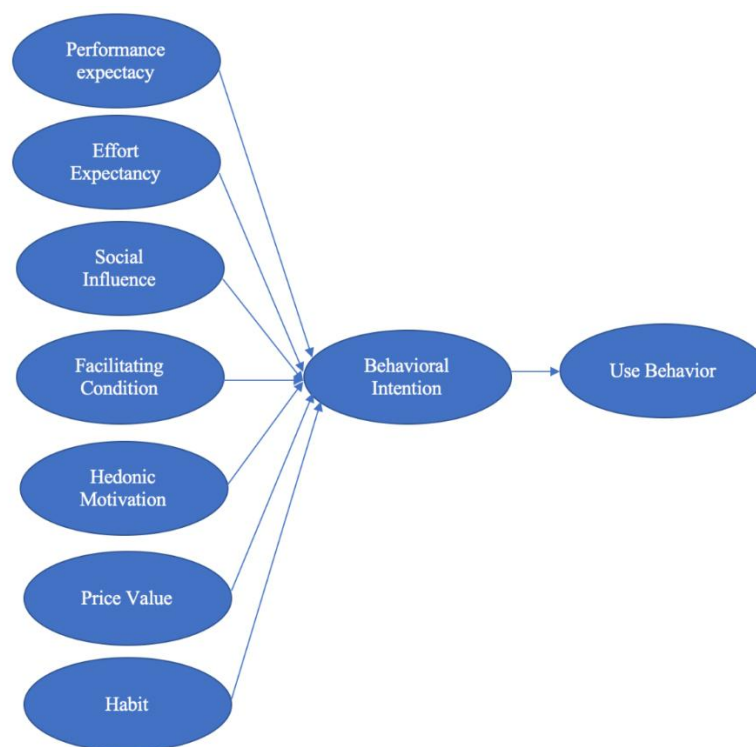
This study specifically examines the influence of performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit on behavioral intention toward AI adoption in Indonesian higher education. More specifically, the study focuses on students enrolled in Indonesian Islamic universities to determine whether the UTAUT2 framework adequately explains AI adoption behavior within a higher education environment characterized by religious values, institutional ethics, and ongoing digital transformation. The objectives of this study are

threefold: (1) to identify the determinants of students' behavioral intention and actual AI use based on the UTAUT2 framework, (2) to evaluate the explanatory capability of UTAUT2 in the context of Indonesian Islamic higher education, and (3) to provide empirical evidence that advances technology acceptance theory within value-based educational institutions. The study contributes theoretically by validating and contextualizing the application of UTAUT2 within AI-based educational systems in an emerging-country context. Empirically, it provides localized evidence regarding AI acceptance behavior among university students in Indonesia, particularly within Islamic higher education, and offers practical implications for policymakers, educators, and technology developers in designing ethical, sustainable, institutionally aligned, and user-centered AI-supported learning environments.

## METHODS

### *Research Design and Hypothesis*

This study employed a quantitative explanatory research design to investigate the determinants of Artificial Intelligence (AI) adoption among university students in Indonesian Islamic higher education institutions. The research framework was developed based on the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) proposed by Venkatesh et al. (2012), which extends the original UTAUT model by incorporating hedonic motivation, price value, and habit to better explain technology adoption behavior. UTAUT2 has been widely validated in studies on AI, digital learning, and educational technology because it integrates cognitive, social, and behavioral factors influencing users' behavioral intention and actual technology use (Acosta-Enriquez et al., 2024; Cabero-Almenara et al., 2024; Grassini et al., 2024; Wijaya & Putra, 2026). In this study, Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Hedonic Motivation (HM), Price Value (PV), and Habit (HB) were specified as exogenous variables affecting Behavioral Intention (BI), which subsequently influences Use Behavior (UB).



**Figure 1.** Research Framework

Based on the UTAUT2 framework (Venkatesh et al., 2012) and previous studies on AI adoption in higher education (Cabero-Almenara et al., 2024; Grassini et al., 2024), this study proposes that students are more likely to adopt AI technologies when they perceive them as useful, easy to use, socially supported, supported by adequate institutional infrastructure, enjoyable, beneficial relative to their costs, and consistent with their habitual technology use. Furthermore, behavioral intention is expected to be the primary predictor of actual AI use. Accordingly, the following hypotheses are proposed:

H1: Performance Expectancy positively influences Behavioral Intention.

H2: Effort Expectancy positively influences Behavioral Intention.

H3: Social Influence positively influences Behavioral Intention.

H4: Facilitating Conditions positively influences Behavioral Intention.

H5: Hedonic Motivation positively influences Behavioral Intention.

H6: Price Value positively influences Behavioral Intention.

H7: Habit positively influences Behavioral Intention.

H8: Behavioral Intention positively influences Use Behavior.

### *Population and Sample*

The population of this study consists of undergraduate students enrolled at Islamic higher education institutions located in Pekanbaru City, Indonesia. This population includes students from various academic disciplines and years of study. The rationale for selecting university students is that they represent the primary users of AI-supported learning technologies and are among the earliest adopters of emerging educational innovations. Islamic universities were specifically chosen because they combine digital transformation initiatives with institutional missions emphasizing Islamic values, ethical responsibility, and character-based education, thereby providing a distinctive context for examining AI adoption behavior.

The sampling method used in this research is probability sampling, ensuring that every eligible student had an equal chance of being selected (Hossan et al., 2023; Moniruzzaman Sarker & AL-Muaalemi, 2022). A list of actively enrolled students was obtained from the academic administration offices of the participating universities and served as the sampling frame. Respondents were selected using a computer-generated simple random sampling procedure after assigning a unique identification number to each eligible student. To ensure representation across different educational environments, the study involved Islamic higher education institutions comprising both public and private universities. Universities were selected based on accessibility, student population size, and the availability of digital learning facilities, as these institutions had already implemented technology-supported learning systems relevant to AI adoption in education.

The inclusion criteria required participants to be actively enrolled undergraduate students who had prior experience using at least one AI-supported learning application (e.g., ChatGPT, AI-based learning assistants, or intelligent educational platforms). Students who had never used AI-assisted learning tools or submitted incomplete questionnaires were excluded from the final analysis.

The sample size was determined using Roscoe's sample size rule, which suggests that a suitable sample size for social science research ranges between 30 and 500 respondents. Following this guideline, a total of 200 students were selected to ensure sufficient representativeness and statistical robustness. In addition, the sample size satisfies the recommendations for Structural Equation Modeling using Partial Least Squares (SEM-PLS), which suggest that a sample exceeding 150

observations is adequate for estimating complex structural models with multiple constructs and indicators (Hair et al., 2021). The sampling technique employed was simple random sampling, allowing each registered student in the selected universities to have an equal probability of being included in the study (Boddy, 2016). This method minimizes sampling bias and ensures a diverse representation of students with different academic backgrounds and technological experiences.

Questionnaires were distributed electronically to 250 students identified through the sampling frame. Prior to full-scale data collection, the questionnaire was reviewed by academic experts and pilot-tested with a small group of students to ensure clarity, readability, and content validity (Baker, 2003; Murphy, 2023). Minor revisions were made based on participant feedback before the final survey was administered. Of the total distributed questionnaires, 214 responses were received, resulting in a response rate of 85.6%. After screening for completeness, duplicate submissions, response consistency, and missing data, 200 valid questionnaires were retained for final analysis.

To examine the possibility of non-response bias, early and late respondents were compared using independent-samples t-tests on the principal study constructs. The results indicated no statistically significant differences ( $p > 0.05$ ), suggesting that non-response bias was unlikely to affect the findings. Furthermore, common method bias (CMB) was assessed using Harman's single-factor test. The first unrotated factor explained less than 50% of the total variance, indicating that common method variance was not a serious concern in this study.

Participation in the study was voluntary. All respondents were informed about the purpose of the research, assured that their responses would remain anonymous and confidential, and provided informed consent before completing the questionnaire.

### *Operational of Variables*

The operational definitions and measurement indicators for each construct in the UTAUT2 model are presented in the following table. These indicators were adapted from (Venkatesh et al., 2012) and supported by more recent studies on AI acceptance in education.

**Table 1. Operational Definition of Variables**

| Variable                | Indicator                                                                                                                                                                                                   | Reference                                              |
|-------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------|
| Performance Expectancy  | 1. AI technology helps improve my learning performance.<br>2. Using AI technology enhances my learning outcomes.<br>3. AI technology helps me achieve my learning goals faster.                             | (Acosta-Enriquez et al., 2024; Venkatesh et al., 2012) |
| Effort Expectancy       | 1. AI technology is easy to understand and use in learning.<br>2. I find it easy to adapt to using AI technology in learning.<br>3. The interface of AI technology is user-friendly and not confusing.      | (Cabero-Almenara et al., 2024; Venkatesh et al., 2012) |
| Social Influence        | 1. My peers encourage me to use AI technology in learning.<br>2. My lecturers support the use of AI technology in learning.<br>3. The institution facilitates the use of AI technology in learning.         | (Grassini et al., 2024; Venkatesh et al., 2012)        |
| Facilitating Conditions | 1. Sufficient technical resources are available to use AI technology.<br>2. Adequate technical support is provided for AI technology use.<br>3. The university's infrastructure supports AI-based learning. | (Ballesteros et al., 2024; Venkatesh et al., 2012)     |
| Hedonic Motivation      | 1. I enjoy and feel interested when using AI technology in learning.                                                                                                                                        | (Cabero-Almenara et al.,                               |

| Variable             | Indicator                                                                 | Reference                                              |
|----------------------|---------------------------------------------------------------------------|--------------------------------------------------------|
| Price Value          | 2. AI technology makes the learning process enjoyable.                    | 2025; Venkatesh et al., 2012)                          |
|                      | 3. AI technology makes learning more engaging.                            |                                                        |
|                      | 1. The benefits of AI technology are worth the cost incurred.             |                                                        |
| Habit                | 2. The cost of using AI technology is reasonable compared to the results. | (Musa et al., 2022; Venkatesh et al., 2012)            |
|                      | 3. Using AI technology provides added value despite the cost.             |                                                        |
|                      | 1. I am accustomed to using technology, including AI, in learning.        |                                                        |
| Behavioral Intention | 2. I automatically use AI technology because it has become a habit.       | (Cabero-Almenara et al., 2024; Venkatesh et al., 2012) |
|                      | 3. I feel comfortable and more productive using AI technology regularly.  |                                                        |
|                      | 1. I intend to use AI technology in future learning activities.           |                                                        |
| Behavioral Intention | 2. I plan to integrate AI technology into my learning process.            | (Grassini et al., 2024; Venkatesh et al., 2012)        |
|                      | 3. I will use AI technology more frequently in future learning.           |                                                        |
|                      |                                                                           |                                                        |

### Data Analysis Technique

The data were analyzed using Descriptive Analysis and Structural Equation Modeling (SEM) with Partial Least Squares (PLS). This dual approach allows for a comprehensive understanding of both respondent characteristics and the causal relationships among variables in the UTAUT2 framework. Descriptive analysis was first conducted to describe the demographic profile of respondents, such as gender, age, and academic discipline, as well as to summarize responses for each variable using measures of central tendency (mean, median, mode) and dispersion (standard deviation). This step provides an overview of students' perceptions toward AI use in higher education. Subsequently, SEM-PLS was employed to test the measurement and structural models. The measurement model was assessed through indicator loadings, composite reliability (CR), Cronbach's Alpha, and Average Variance Extracted (AVE). Indicators with loading values above 0.70, CR and Alpha above 0.70, and AVE above 0.50 were considered valid and reliable. Next, the structural model was analyzed to examine the hypothesized relationships among constructs using path coefficients and their significance levels obtained via bootstrapping. Path coefficients with  $t$ -values above 1.96 ( $p < 0.05$ ) were considered significant. Model explanatory power was evaluated using  $R^2$ , while  $f^2$  was used to determine the effect size of each predictor variable. The behavioral intention variable was also tested as a mediator between predictor constructs and potential user behavior, using indirect effect testing and bootstrapping procedures. Finally, model fit was evaluated using the Standardized Root Mean Square Residual (SRMR) criterion, with a value below 0.08 indicating an acceptable level of model fit (Hair et al., 2021).

## FINDINGS AND DISCUSSION

### Respondent Characteristics

This study involved 200 respondents classified by gender and field of study. The analysis of respondent characteristics was conducted to identify the demographic distribution of the research sample, thereby providing an initial overview of the representation of the study population. Based on gender, the respondents consisted of male and female students, while in terms of field of study, they were categorized into Social Sciences and Natural Sciences. This distribution is important to ensure a variety of perspectives in the data collected.

**Table 2. Respondent Characteristics by Gender and Field of Study (n = 200)**

| Characteristic        | Frequency (f) | Percentage (%) |
|-----------------------|---------------|----------------|
| <b>Gender</b>         |               |                |
| Male                  | 96            | 48.2           |
| Female                | 104           | 51.8           |
| <b>Field of Study</b> |               |                |
| Social Sciences       | 113           | 56.7           |
| Natural Sciences      | 87            | 43.3           |
| <b>Total</b>          | <b>200</b>    | <b>100.0</b>   |

Based on Table 2, the number of female respondents (104 or 51.8%) is slightly higher than that of male respondents (96 or 48.2%), indicating a relatively balanced gender distribution in this study. In terms of academic disciplines, the majority of respondents came from the Social Sciences (113 or 56.7%), while 87 respondents (43.3%) were from the Natural Sciences. This distribution shows that while students from Social Sciences dominate the sample, there remains sufficient diversity to represent various academic fields in Pekanbaru's higher education institutions.

### *Instrument Validity and Reliability Testing*

Before conducting the analysis of relationships among variables using SEM-PLS, validity and reliability tests were carried out to ensure that all indicators used in the study accurately and consistently measure the intended constructs.

### *Convergent Validity*

Convergent validity was examined through outer loadings. An indicator is considered valid if its loading factor is  $\geq 0.7$ , which indicates that the item adequately represents the intended latent variable. The results of the SEM-PLS analysis are presented in Table 3.

**Table 3. Validity Test Results (Outer Loading)**

| Variable                | Indicator | Outer Loading | Conclusion |
|-------------------------|-----------|---------------|------------|
| Performance Expectancy  | PE1       | 0.812         | Valid      |
|                         | PE2       | 0.839         | Valid      |
|                         | PE3       | 0.825         | Valid      |
| Effort Expectancy       | EE1       | 0.804         | Valid      |
|                         | EE2       | 0.792         | Valid      |
|                         | EE3       | 0.777         | Valid      |
| Social Influence        | SI1       | 0.815         | Valid      |
|                         | SI2       | 0.828         | Valid      |
|                         | SI3       | 0.801         | Valid      |
| Facilitating Conditions | FC1       | 0.803         | Valid      |
|                         | FC2       | 0.810         | Valid      |
|                         | FC3       | 0.792         | Valid      |
| Hedonic Motivation      | HM1       | 0.822         | Valid      |
|                         | HM2       | 0.835         | Valid      |
|                         | HM3       | 0.818         | Valid      |
| Price Value             | PV1       | 0.811         | Valid      |
|                         | PV2       | 0.798         | Valid      |
|                         | PV3       | 0.805         | Valid      |

|                      |     |       |       |
|----------------------|-----|-------|-------|
| Habit                | H1  | 0.820 | Valid |
|                      | H2  | 0.833 | Valid |
|                      | H3  | 0.810 | Valid |
| Behavioral Intention | BI1 | 0.838 | Valid |
|                      | BI2 | 0.845 | Valid |
|                      | BI3 | 0.832 | Valid |

As shown in Table 3, all indicators have outer loading values  $\geq 0.7$ , indicating that each indicator is valid and convergently represents the associated variable. This means that all questionnaire items effectively measure their intended constructs, and no items need to be removed or revised. The results confirm that the research instrument meets the initial measurement quality requirements before further analysis.

### ***Discriminant Validity***

Discriminant validity was evaluated using the Heterotrait–Monotrait Ratio (HTMT). According to (Henseler et al., 2015), an HTMT value below 0.90 indicates adequate discriminant validity among constructs. Table 4 presents the HTMT results.

**Table 4. HTMT Results**

| Variable  | PE    | EE    | SI    | FC    | HM    | PV    | H     | BI |
|-----------|-------|-------|-------|-------|-------|-------|-------|----|
| <b>PE</b> | –     |       |       |       |       |       |       |    |
| <b>EE</b> | 0.641 | –     |       |       |       |       |       |    |
| <b>SI</b> | 0.573 | 0.612 | –     |       |       |       |       |    |
| <b>FC</b> | 0.684 | 0.592 | 0.563 | –     |       |       |       |    |
| <b>HM</b> | 0.715 | 0.634 | 0.551 | 0.628 | –     |       |       |    |
| <b>PV</b> | 0.562 | 0.601 | 0.527 | 0.574 | 0.642 | –     |       |    |
| <b>H</b>  | 0.742 | 0.654 | 0.591 | 0.673 | 0.718 | 0.617 | –     |    |
| <b>BI</b> | 0.803 | 0.681 | 0.624 | 0.721 | 0.764 | 0.635 | 0.784 | –  |

Discriminant validity (Table 4) was assessed using the Heterotrait–Monotrait Ratio (HTMT). According to (Henseler et al., 2015), an HTMT value below 0.90 indicates adequate discriminant validity among constructs. Table 4 shows that all HTMT values are below the recommended threshold value of 0.90. Therefore, the constructs demonstrate satisfactory discriminant validity, indicating that each construct is empirically distinct and measures different conceptual dimensions within the proposed model.

### ***Reliability Test***

After confirming indicator validity, the next step was to test the reliability of the constructs to ensure internal consistency among indicators. Reliability was assessed using Composite Reliability (CR) and Average Variance Extracted (AVE). A construct is considered reliable if  $CR \geq 0.7$  and A construct is considered valid in terms of convergent validity if  $AVE \geq 0.5$ .

**Table 5. Reliability Test Results**

| Variable                | CR    | AVE   | Conclusion       |
|-------------------------|-------|-------|------------------|
| Performance Expectancy  | 0.867 | 0.678 | Reliable & Valid |
| Effort Expectancy       | 0.853 | 0.662 | Reliable & Valid |
| Social Influence        | 0.860 | 0.670 | Reliable & Valid |
| Facilitating Conditions | 0.854 | 0.661 | Reliable & Valid |
| Hedonic Motivation      | 0.872 | 0.681 | Reliable & Valid |
| Price Value             | 0.857 | 0.668 | Reliable & Valid |
| Habit                   | 0.870 | 0.679 | Reliable & Valid |
| Behavioral Intention    | 0.875 | 0.685 | Reliable & Valid |

Table 5 shows that all constructs have  $CR > 0.7$  and  $AVE > 0.5$ , indicating good internal consistency and convergent validity. Therefore, the research instrument is both reliable and valid, making it appropriate for use in SEM-PLS analysis and hypothesis testing. These results confirm that the questionnaire data are dependable and accurately reflect the studied constructs, ensuring robust model estimation.

#### ***Multicollinearity Test (Variance Inflation Factor / VIF)***

The multicollinearity test was performed to verify that the independent variables were not excessively correlated with one another, as high intercorrelation could distort the estimation of path coefficients in SEM-PLS. In this analysis,  $VIF < 5$  is considered acceptable.

**Table 6. Multicollinearity Test (VIF)**

| Independent Variable         | VIF  | Conclusion           |
|------------------------------|------|----------------------|
| Performance Expectancy (PE)  | 1.82 | No multicollinearity |
| Effort Expectancy (EE)       | 1.75 | No multicollinearity |
| Social Influence (SI)        | 1.67 | No multicollinearity |
| Facilitating Conditions (FC) | 1.60 | No multicollinearity |
| Hedonic Motivation (HM)      | 1.90 | No multicollinearity |
| Price Value (PV)             | 1.85 | No multicollinearity |
| Habit (H)                    | 2.05 | No multicollinearity |

As shown in Table 6, all VIF values range between 1.60 and 2.05, well below the critical threshold of 5. This indicates the absence of multicollinearity among independent variables, confirming that each predictor contributes uniquely to explaining variance in Behavioral Intention (BI). Hence, the SEM-PLS results can be considered reliable.

#### ***Coefficient of Determination (R-Square)***

The R-Square ( $R^2$ ) value measures the proportion of variance in the dependent variable explained by the independent variables. Higher  $R^2$  values indicate stronger explanatory power. Behavioral Intention (BI):  $R^2 = 0.721$ , meaning that 72.1% of the variance in students' behavioral intention to use AI technology is explained by Performance Expectancy, Effort Expectancy, Social Influence, Facilitating

Conditions, Hedonic Motivation, Price Value, and Habit, while 27.9% is explained by other factors outside the model. Use Behavior (UB):  $R^2 = 0.428$ , meaning that 42.8% of the variance in actual use behavior is explained by Behavioral Intention.

### *Effect Size (F-Square)*

The F-Square ( $f^2$ ) test evaluates the effect size of each independent variable on the dependent variable. Common criteria are: 0.02 = small effect, 0.15 = medium effect and 0.35 = large effect

**Table 7. F-Square Results**

| <b>Independent → Dependent</b> | <b><math>f^2</math></b> | <b>Effect</b> |
|--------------------------------|-------------------------|---------------|
| PE → BI                        | 0.102                   | Small         |
| EE → BI                        | 0.065                   | Small         |
| SI → BI                        | 0.041                   | Small         |
| FC → BI                        | 0.029                   | Small         |
| HM → BI                        | 0.086                   | Small         |
| PV → BI                        | 0.052                   | Small         |
| H → BI                         | 0.095                   | Small         |
| BI → UB                        | 0.745                   | Large         |

As shown in Table 7, Behavioral Intention has a substantial effect on Use Behavior ( $f^2 = 0.745$ ), whereas other variables exhibit small but meaningful effects on Behavioral Intention.

### *Predictive Relevance ( $Q^2$ )*

Predictive relevance was evaluated using the Stone–Geisser  $Q^2$  value through the blindfolding procedure. According to (Sabol et al., 2023),  $Q^2$  values greater than zero indicate predictive relevance, while values of 0.02, 0.15, and 0.35 indicate small, medium, and large predictive relevance, respectively. From this results, the Behavioral Intention construct demonstrates a  $Q^2$  value of 0.504, indicating strong predictive relevance. Meanwhile, Use Behavior exhibits a  $Q^2$  value of 0.238, reflecting moderate predictive relevance. These results suggest that the proposed model possesses adequate predictive capability in explaining students' intention and actual behavior toward AI technology adoption in higher education.

### *Hypothesis Testing Using SEM-PLS*

Hypothesis testing was conducted using path coefficients,  $t$ -statistics, and  $p$ -values obtained through the bootstrapping procedure in the SEM-PLS analysis. The criteria for determining statistical significance were  $t$ -statistic values greater than 1.96 and  $p$ -values less than 0.05, indicating significance at the 5% level.

**Table 8. Hypothesis Testing Results**

| Hypothesis                                         | Path Coefficient | t-statistic | p-value | Conclusion      |
|----------------------------------------------------|------------------|-------------|---------|-----------------|
| H1: Performance Expectancy → Behavioral Intention  | 0.312            | 3.85        | 0.000   | Significant     |
| H2: Effort Expectancy → Behavioral Intention       | 0.145            | 1.62        | 0.106   | Not significant |
| H3: Social Influence → Behavioral Intention        | 0.098            | 1.10        | 0.272   | Not significant |
| H4: Facilitating Conditions → Behavioral Intention | 0.154            | 2.01        | 0.045   | Significant     |
| H5: Hedonic Motivation → Behavioral Intention      | 0.274            | 3.35        | 0.001   | Significant     |
| H6: Price Value → Behavioral Intention             | 0.121            | 1.45        | 0.148   | Not significant |
| H7: Habit → Behavioral Intention                   | 0.301            | 3.70        | 0.000   | Significant     |
| H8: Behavioral Intention → Use Behavior            | 0.654            | 8.92        | 0.000   | Significant     |

The results indicate that five out of eight hypotheses are supported, demonstrating that several key variables significantly influence the behavioral intention to use Artificial Intelligence (AI) technology in higher education learning. Specifically, Performance Expectancy, Facilitating Conditions, Hedonic Motivation, and Habit have a significant positive effect on Behavioral Intention, while Behavioral Intention significantly influences Use Behavior. This finding implies that when students perceive that AI enhances their learning performance, are supported by adequate technological infrastructure, find the learning process enjoyable, and have already established habitual technology use, their intention to continue using AI in learning activities increases substantially. In contrast, Effort Expectancy, Social Influence, and Price Value do not show a significant effect on Behavioral Intention. This suggests that the perceived ease of use, external social pressure, and cost-benefit considerations are not decisive determinants in students' adoption of AI technology. The non-significance of these factors may indicate that university students, who are generally digital natives, already possess sufficient technological literacy and independence in adopting new technologies without needing external motivation or strong consideration of effort or cost. Overall, the findings highlight that while not all UTAUT2 variables are universally influential, the most critical determinants of AI acceptance in higher education are usefulness, enjoyment, and habitual use. These factors strongly shape students' behavioral intentions, which in turn directly predict their actual use of AI in the learning environment. This confirms that intrinsic motivation and perceived value play a more dominant role in driving technology adoption among students in contemporary digital learning ecosystems.

## Discussion

The findings provide important insights into the factors influencing Artificial Intelligence (AI) adoption among students in Indonesian Islamic higher education institutions based on the UTAUT2 framework (Helmiatin et al., 2024; Indasari, 2026). Five of the eight proposed hypotheses were supported, indicating that performance expectancy, facilitating conditions, hedonic motivation, and habit significantly influence behavioral intention, while behavioral intention strongly predicts actual AI use. Rather than simply confirming statistical relationships, these findings reveal that students' AI adoption is primarily driven by their perceptions of educational value, meaningful learning experiences, and routine engagement with AI technologies rather than by external pressures or technological characteristics alone. This pattern suggests a shift from technology-oriented acceptance toward value-oriented acceptance, in which students evaluate AI based on its contribution to learning effectiveness, problem-solving, and academic development. As students become increasingly digitally competent, technology adoption decisions are shaped more by perceived pedagogical value than by the novelty of the technology itself (Hutahaeen et al., 2023; Ichsan et al., 2024; Susanti et al., 2024).

The results demonstrate that performance expectancy has a significant positive influence on behavioral intention. Students who believe that AI improves learning efficiency, academic performance, and problem-solving capabilities are more willing to integrate AI into their learning activities. This finding indicates that students no longer perceive AI merely as an emerging technology but as an integral component of their academic learning ecosystem. The significant effect of performance expectancy reflects students' expectations that AI should deliver tangible educational benefits, such as personalized learning support, faster access to information, and improved academic productivity. Consequently, perceived usefulness extends beyond operational efficiency to encompass meaningful learning enhancement. This interpretation is consistent with (Alshammari & Babu, 2025; Kamenov, 2025), who reported that perceived usefulness strongly predicts students' intention to use ChatGPT, and (Romero-Rodríguez et al., 2023; Sallam et al., 2024), who emphasized AI's role in supporting personalized learning. Theoretically, these findings reinforce the central proposition of UTAUT2 while suggesting that the concept of performance expectancy should increasingly be interpreted within the broader context of adaptive and personalized learning environments.

In contrast, effort expectancy was not found to significantly influence behavioral intention. Rather than indicating that ease of use is unimportant, this finding suggests that ease of use has become a basic expectation among contemporary university students who possess high levels of digital literacy and technological confidence. For Generation Z learners, intuitive interfaces and user-friendly applications are considered standard characteristics of educational technologies rather than factors differentiating adoption decisions. As a result, students focus more on whether AI provides meaningful academic value than on how easy it is to operate. This interpretation supports the notion that the explanatory power of effort expectancy may gradually decline as digital technologies become more familiar and users develop greater technological self-efficacy.

Similarly, social influence did not significantly affect behavioral intention. This finding indicates that AI adoption has become increasingly individualized, with students relying primarily on personal experience and independent evaluation rather than on recommendations from lecturers, peers, or institutional authorities. Unlike previous educational technologies that often required institutional encouragement, generative AI applications are widely accessible and can be explored independently. Consequently, students evaluate AI according to its direct contribution to their own learning rather

than external social expectations. This interpretation aligns with (Graafsma et al., 2022; Granić & Marangunić, 2019; Mutaqin et al., 2026), who argued that younger generations increasingly demonstrate autonomous digital behaviors. Theoretically, these findings suggest that the role of social influence may diminish in learning environments where students possess greater autonomy in selecting and utilizing digital technologies.

The significant influence of facilitating conditions demonstrates that institutional readiness remains an essential prerequisite for AI adoption. Students are more willing to adopt AI when supported by reliable internet access, appropriate learning platforms, and adequate technical assistance. However, facilitating conditions should not be interpreted solely as technological infrastructure. They also represent institutional commitment to integrating AI responsibly through training programs, digital governance, academic support, and clear implementation policies. Such institutional support strengthens students' confidence in using AI while reducing uncertainty associated with emerging technologies. These findings therefore extend the original UTAUT2 perspective by emphasizing that organizational readiness remains fundamental for sustainable AI integration in higher education.

Hedonic motivation also significantly influenced behavioral intention, indicating that enjoyable and engaging learning experiences contribute substantially to AI adoption. This finding highlights that AI-supported learning combines cognitive and affective dimensions, where students are motivated not only by academic outcomes but also by enjoyable interactions with intelligent systems. Conversational AI applications, such as ChatGPT, create interactive learning experiences that enhance engagement, curiosity, and learning satisfaction. Therefore, emotional engagement should be regarded as an essential component of effective AI-supported pedagogy rather than merely a complementary feature of educational technology. This interpretation is consistent with previous studies demonstrating that intrinsic motivation strengthens students' willingness to continue using AI in educational settings.

Conversely, price value did not significantly influence behavioral intention. One plausible explanation is that many AI applications currently provide free or institutionally supported services that adequately meet students' academic needs. Consequently, students rarely perceive financial cost as a major consideration when deciding whether to adopt AI. Instead, they prioritize educational usefulness, learning quality, and user experience. This finding suggests that economic considerations become less influential once barriers to technology access are substantially reduced. Accordingly, the explanatory relevance of the price value construct may decrease in educational environments where AI technologies are readily accessible.

Habit emerged as another significant predictor of behavioral intention. This finding demonstrates that sustainable AI adoption develops through repeated academic use rather than through one-time exposure. Frequent interaction with AI systems gradually increases familiarity, confidence, and reliance on these technologies, transforming AI use into routine academic behavior. Habit therefore functions as a mechanism that supports long-term technology adoption by reducing uncertainty and reinforcing continued engagement with AI-assisted learning. This interpretation indicates that universities should encourage continuous rather than occasional AI use within learning activities.

The contextual implications of these findings are particularly important for Indonesian Islamic higher education institutions. Unlike many studies conducted in technologically advanced Western contexts, AI adoption within Indonesian Islamic universities occurs in educational environments that emphasize religious values, ethical responsibility, critical thinking, and character development

alongside technological innovation. Although these dimensions were not directly measured in the present study, they provide a meaningful contextual explanation for why intrinsic motivational factors were more influential than external social or economic factors. Students appear to evaluate AI primarily according to whether it enhances meaningful learning while remaining consistent with institutional educational values. Consequently, technology acceptance in Islamic higher education should be interpreted not only through technological perspectives but also through pedagogical, ethical, and sociocultural lenses (Gustinov et al., 2023; Supriyadi et al., 2025).

Finally, behavioral intention demonstrated a strong positive influence on actual use behavior, confirming one of the central assumptions of UTAUT2 that intention remains the most immediate determinant of technology use. This finding indicates that strengthening students' motivation, perceived educational value, and confidence in AI technologies will likely translate into sustained adoption and integration within academic activities. Universities therefore need to move beyond simply introducing AI technologies toward creating educational environments that encourage meaningful and continuous AI-supported learning.

Overall, these findings refine the application of UTAUT2 by demonstrating that the relative importance of its constructs changes as educational technologies become more mature and familiar to users. Traditional determinants such as effort expectancy and social influence become less influential, whereas intrinsic motivation, perceived educational value, and habitual engagement emerge as the dominant drivers of AI adoption. Furthermore, the study extends technology acceptance research by showing that AI adoption within Indonesian Islamic higher education reflects the interaction between technological capabilities, institutional support, and value-oriented educational contexts. These findings suggest that future extensions of UTAUT2 should incorporate contextual constructs such as trust in AI, AI ethics, AI literacy, privacy concerns, and institutional governance to better explain AI adoption in higher education.

## CONCLUSION

This study investigated the determinants of Artificial Intelligence (AI) adoption among students in Indonesian Islamic higher education institutions using the UTAUT2 framework. The findings indicate that performance expectancy, facilitating conditions, hedonic motivation, and habit significantly influence students' behavioral intention to use AI, while behavioral intention strongly predicts actual use behavior. Conversely, effort expectancy, social influence, and price value do not significantly affect behavioral intention. These results suggest that students' AI adoption is driven primarily by perceived academic benefits, institutional support, intrinsic enjoyment, and habitual technology use rather than by ease of use, social pressure, or cost considerations.

The study contributes to the literature by validating the applicability of UTAUT2 in the context of AI-supported learning within Indonesian Islamic higher education. It demonstrates that intrinsic motivational factors and habitual technology use have become more influential than several traditional technology acceptance determinants in explaining AI adoption. The findings also provide practical implications for higher education institutions by highlighting the importance of strengthening digital infrastructure, promoting responsible AI integration into teaching and learning, and designing learning environments that encourage sustained and meaningful engagement with AI technologies.

However, this study has several limitations. First, the cross-sectional research design captures students' perceptions at a single point in time and therefore cannot explain how AI adoption behavior

evolves as students gain greater experience with AI technologies. Second, the study was conducted only among students from Islamic higher education institutions in Pekanbaru, which may limit the generalizability of the findings to other regions, institutional types, or cultural contexts. Third, the data were collected using self-reported questionnaires, making the results susceptible to common method bias and social desirability bias despite the procedural measures adopted during data collection. Finally, the study focused exclusively on the original UTAUT2 constructs and did not incorporate other emerging factors that may shape AI acceptance in educational settings, such as trust, AI ethics, privacy concerns, and AI literacy.

Future research should employ longitudinal research designs to examine changes in students' AI adoption behavior over time and to investigate the long-term effects of AI use on learning outcomes. Comparative studies involving universities from different regions, countries, or institutional characteristics are also recommended to improve the external validity and generalizability of the findings. Moreover, future studies should extend the UTAUT2 framework by incorporating additional constructs, including trust in AI, AI ethics, privacy concerns, algorithmic transparency, AI literacy, and institutional AI governance, to provide a more comprehensive explanation of AI acceptance in higher education. Finally, qualitative or mixed-method approaches are recommended to explore how students' experiences, ethical considerations, and institutional values influence the sustainable adoption of AI-supported learning technologies.

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