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PERCEPTION OF THE AI USE: IN UNDERSTANDING ENGLISH ISLAMIC EDUCATION LITERATURES BY ISLAMIC EDUCATION STUDENTS

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Abstract: This study aimed to analyze the perception of the use of Artificial Intelligence (AI) in helping Islamic Education students at PTKIN in Central Java to understand English-language Islamic education literature. The study used a quantitative approach, a survey method, and analyzed using the Technology Acceptance Model (TAM) modified with Computer Self-Efficacy (CSE) variables. The sample consisted of 100 Islamic Education students from six State Islamic Religious Colleges (PTKIN) in Central Java. Partial Least Squares–Structural Equation Modeling (PLS-SEM) was used to analyze the data. The results showed that Computer Self-Efficacy had a significant effect on Perceived Ease of Use ($t = 9.556$; $p < 0.001$) and Perceived Usefulness ($t = 5.912$; $p < 0.001$). Perceived Ease of Use had a significant effect on Perceived Usefulness ($t = 7.313$; $p < 0.001$) and Attitude Toward Using ($t = 5.108$; $p < 0.001$). Perceived Usefulness also significantly influences Attitude Toward Using ($t = 8.183$; $p < 0.001$). Furthermore, Attitude Toward Using significantly influenced Behavioral Intention to Use ($t = 9.095$; $p < 0.001$), and Behavioral Intention to Use significantly influences Actual System Use ($t = 16.280$; $p < 0.001$). However, the effect of Perceived Usefulness on Behavioral Intention to Use is not significant ($t = 1.623$; $p = 0.105$). These findings confirm that technology confidence and the ease of use of AI are key factors in AI utilization among Islamic Education students. The implication of this study confirms that digital competence and the ease of AI use influence Islamic Education students' acceptance of AI in understanding English-language literature.

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INTRODUCTION

Artificial Intelligence (AI) has become one of the most transformative technologies of the 21st century. In education, AI has been used to improve learning efficiency, personalize learning materials, and help students understand complex content (Bauer et al., 2025; Belkhir, 2024; Grassini, 2023). According to Alshahrani & Qureshi (2024) and Mannuru et al. (2023), AI has great potential to

revolutionize higher education by providing innovative solutions such as intelligent tutoring systems, adaptive learning analytics, and language support tools. However, user acceptance and perception of this technology are critical factors in determining its implementation success. Crawford et al. (2023) and Liu et al. (2025) stated AI has also been used to assist students in understanding foreign literature, including English-language texts. Tools such as Google Translate, ChatGPT, and applications based on Natural Language Processing (NLP) have made it easier for students to translate and summarize academic texts. One application of QuillBot is to summarize and simplify complex content. However, the effectiveness of AI in Islamic education still requires further investigation, particularly regarding students' perceptions of this technology.

Islamic Education students often struggle to understand English-language literature. Several factors, including limited proficiency in foreign languages, limited access to adequate learning resources, low literacy among student's and differences in cultural contexts between Western and Islamic literature, cause this. Students of Islamic Education frequently found it difficult to comprehend English-language literature due to insufficient language proficiency and a lack of technological support for the learning process. This pedagogical gap is often worsened by a lack of specialized English training tailored to Islamic studies terminology, leaving students reliant on slow, conventional translation methods. Consequently, this literacy barrier drastically restricted their academic mobility, lowering their confidence in international discourse and limiting their ability to engage critically with high-impact global research essential for advancing modern Islamic education. In this context, AI can address these challenges by providing tools for translation, automatic summarization, and explanations of key concepts.

Furthermore, AI can also be used to identify key concepts in Islamic education literature and provide explanations that are easier to understand. Therefore, in addition to ensuring alignment with Islamic values and maintaining students' critical thinking skills, it is also important to understand how students' perceptions of AI may influence the effectiveness of this technology in education. According to Kim et al. (2025) and Panmei (2025), in the Technology Acceptance Model (TAM), users' perceptions of ease of use and usefulness are the main predictors of technology acceptance. Several previous studies have examined students' perceptions of AI in education. Chiu et al. (2024) and Kim (2024) found that students tend to have positive perceptions of AI when they believe it can improve learning efficiency and help them achieve academic goals. The students have concerns about the reliability and data security of AI use.

Again, Rani et al. (2025) and Schiff (2023) studies have shown that AI offers significant benefits, including personalized learning, improved academic outcomes, and increased student engagement. In addition, research by Ab Alim et al. (2025) and Issa & Hall (2024) reveals that students' perceptions of AI are influenced by factors such as ease of use, usefulness, and trust in the technology. Furthermore, recent scholarship indicates that when AI tools are integrated with pedagogical scaffolding, they significantly mitigate cognitive overload and

accelerate academic reading comprehension among non-native English speakers. Longitudinal data also substantiates that institutions adopting ethical AI frameworks experience a notable rise in student trust and sustained digital literacy proficiency. The findings of these studies are also relevant to the regulations outlined in the Circular Letter of the Minister of Communication and Informatics Number 9 of 2023 (Mohammed et al., 2024; Strielkowski et al., 2025), which emphasizes the importance of responsible and ethical use of AI, including in the education sector.

This study specifically examined the perceptions of Islamic Education students at PTKIN in Central Java toward the utilization of AI in understanding English-language Islamic education literature by using the Technology Acceptance Model (TAM) and Computer Self-Efficacy approaches. Unlike previous studies that discussed AI in general contexts, this research focuses on the context of Islamic education and English academic literature. By merging TAM with Computer Self-Efficacy, this inquiry moves beyond mere technological adoption to chart how digital self-beliefs directly govern the comprehension of specialized, cross-cultural academic texts. The unique intersection of Islamic pedagogy and foreign-language literature addresses a critical gap in current digital humanities, where non-Western educational contexts remain significantly underrepresented. Investigating this nexus is highly urgent; as higher education rapidly digitizes, understanding these specific dynamics is vital for creating ethical, targeted AI integration strategies that prevent minority academic disciplines from falling behind in global digital literacy. Therefore, this study aimed to analyze Islamic Education students' perceptions of AI utilization and the factors influencing those perceptions.

RESEARCH METHOD

The model used in this study is the Technology Acceptance Model (TAM). It is a model of information technology system acceptance that users will use. It was developed by Davis in 1989 based on the TRA (Theory of Reasoned Action) model (Bauer et al., 2025; Belkhir, 2024; Hamadi & El-Den, 2024). Although the TAM was first introduced by Davis in 1989, it remains relevant and is still used in various studies today to predict user acceptance of interactive technology in information systems studies. In TAM research, external variables, namely Computer Self-Efficacy (CSE), are used to analyze users' technology acceptance. These variables are: Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Attitude Toward Using (ATU), Behavioral Intention to Use (BITU), and Actual System Use (AU). The scheme for each variable is as follows:

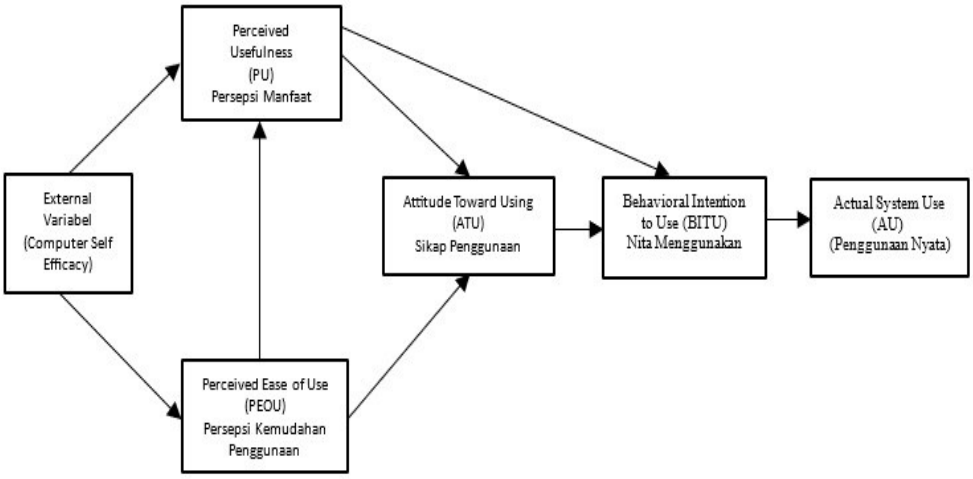

Figure 1. Technology Acceptance Model

The populations in this study were Islamic Education students at six Islamic state universities in Central Java: Salatiga State Islamic University, Walisongo State Islamic University in Semarang, Raden Mas Said State Islamic University in Surakarta, K.H. Saifudin Zuhri State Islamic University in Purwokerto, K.H. Abdurrahman Wahid State Islamic University in Pekalongan, and Kudus State Islamic Institute. The sample size represents a subset of the population and its characteristics. The sample size used was 20 observations per variable; therefore, a minimum sample size of 100 individuals.

Based on the conceptual framework, the relationships between variables in this study were formulated into several hypotheses as follows.
H1: Computer self-efficacy influences perceptions of technology use.
H2: Computer self-efficacy influences perceptions of technology use.
H3: Perceived ease of use of technology influences perceptions of usefulness.
H4: Perceived usefulness influences attitudes toward using technology.
H5: Perceived ease of use of technology influences attitudes.
H6: Perceived usefulness influences intentions to use technology.
H7: Attitude influences intentions to use technology.
H8: Attitude and intention to use influence frequency of use.

RESULT AND DISCUSSION

Result

Measurement Model Test (Outer Model)

Validity testing is conducted to determine whether all proposed research instruments for measuring the constructs are valid. Convergent validity in PLS with reflective indicators is assessed using the loadings. The loading factor criterion is 0.7 or higher. Another measure of convergent validity is the Average Variance Extracted (AVE). Indicators with an AVE value above 0.5 are considered valid.

To measure the outer model, there are two stages: a validity test using convergent validity.

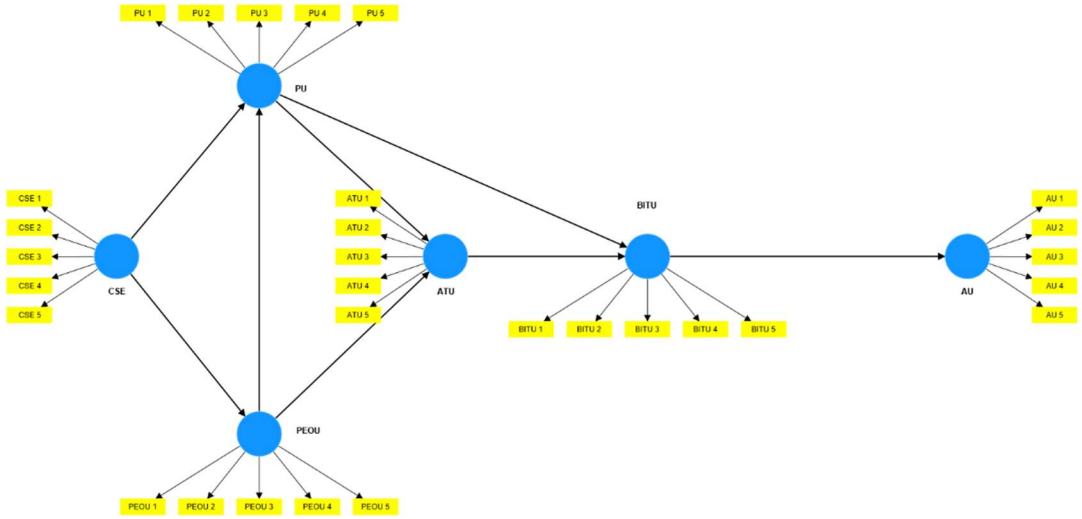

Figure 2. Research Model in SmartPLS

The figure shows the Extended Technology Acceptance Model (TAM), which is used to analyze factors that influence the acceptance and use of a technology by users. In this model, Computer Self-Efficacy (CSE) acts as an external variable that describes the user's level of confidence in using a computer or technology, which then influences Perceived Ease of Use (PEOU). PEOU also influences Perceived Usefulness (PU), which is the user's perception of the benefits obtained from using the system. These two variables then form Attitude Toward Using (ATU), which then influences Behavioral Intention to Use (BTU), which is the intention to use the system. Ultimately, this intention will determine Actual Use (AU), or the user's actual use of the system. Each construct is measured by five indicators, namely CSE1–CSE5, PEOU1–PEOU5, PU1–PU5, ATU1–ATU5, BTU1–BTU5, and AU1–AU5, which function as question items in the research questionnaire.

Validity Test

Convergent validity is assessed by the loading factor, which represents each indicator's value. The criterion for the loading factor is greater than 0.7, and the Average Variance Extracted (AVE) should be greater than 0.5. In the SmartPLS application, the process is carried out in two stages: first, after the measurement model is established, and second, by performing calculations using the PLS Algorithm.

Table 1. Outer Loading Indicator in Variables in the Research Phase 1

Variable	Indicator	Loading Factor	Level of *Convergen Validity*	Explanation
Computer Self-Efficacy (CSE	CSE 1	0.682	0.7	Invalid
	CSE 2	0.681	0.7	Invalid
	CSE 3	0.673	0.7	Invalid
	CSE 4	0.764	0.7	Valid
	CSE 5	0.764	0.7	Valid
Attitude Toward Using	ATU 1	0.817	0.7	Valid
	ATU 2	0.854	0.7	Valid

	ATU 3	0.778	0.7	Valid
	ATU 4	0.813	0.7	Valid
	ATU 5	0.809	0.7	Valid
	AU 1	0.824	0.7	Valid
Actual System Use (AU)	AU 2	0.710	0.7	Valid
	AU 3	0.705	0.7	Valid
	AU 4	0.833	0.7	Valid
	AU 5	0.703	0.7	Valid
	BITU 1	0.793	0.7	Valid
Behavioral Intention to Use (BITU)	BITU 2	0.778	0.7	Valid
	BITU 3	0.801	0.7	Valid
	BITU 4	0.724	0.7	Valid
	BITU 5	0.765	0.7	Valid
	PEOU 1	0.887	0.7	Valid
Perceived Ease of Use (PEOU)	PEOU 2	0.859	0.7	Valid
	PEOU 3	0.838	0.7	Valid
	PEOU 4	0.903	0.7	Valid
	PEOU 5	0.862	0.7	Valid
	PU 1	0.761	0.7	Valid
Perceived Usefulness (PU)	PU 2	0.812	0.7	Valid
	PU 3	0.867	0.7	Valid
	PU 4	0.831	0.7	Valid
	PU 5	0.794	0.7	Valid

The results of the convergent validity test showed that three indicators did not initially meet the established criteria, as their loadings were below 0.7. Indicators with values below 0.7 must be removed from the model. The indicators removed were: CSE Indicator 1 with an outer loading of 0.682, CSE Indicator 2 with an outer loading of 0.681, and CSE Indicator 3 with an outer loading of 0.673. This step demonstrates the thoroughness of the process, reassuring researchers that only valid indicators are retained, which should strengthen confidence in the results. Therefore, a second stage of the convergent validity test was conducted to obtain results that satisfy the construct validity criteria.

Table 2. Outer Loading Indicator in Variables in the Research Phase 2

Variable	Indicator	Loading Factor	Level of *Convergen Validity*	Explanation
Computer Self-Efficacy (CSE	CSE 4	0.854	0.7	Valid
	CSE 5	0.844	0.7	Valid
	ATU 1	0.817	0.7	Valid
Attitude Toward Using	ATU 2	0.854	0.7	Valid
	ATU 3	0.778	0.7	Valid
	ATU 4	0.813	0.7	Valid
	ATU 5	0.809	0.7	Valid
	AU 1	0.824	0.7	Valid
Actual System Use (AU)	AU 2	0.710	0.7	Valid
	AU 3	0.705	0.7	Valid
	AU 4	0.813	0.7	Valid
	AU 5	0.809	0.7	Valid
	BITU 1	0.793	0.7	Valid
Behavioral Intention to Use (BITU)	BITU 2	0.778	0.7	Valid
	BITU 3	0.801	0.7	Valid
	BITU 4	0.724	0.7	Valid

Variable	Indicator	Loading Factor	Level of *Convergen Validity*	Explanation
Perceived Ease of Use (PEOU)	BITU 5	0.765	0.7	Valid
	PEOU 1	0.888	0.7	Valid
	PEOU 2	0.860	0.7	Valid
	PEOU 3	0.838	0.7	Valid
	PEOU 4	0.903	0.7	Valid
	PEOU 5	0.8061	0.7	Valid
Perceived Usefulness (PU)	PU 1	0.761	0.7	Valid
	PU 2	0.812	0.7	Valid
	PU 3	0.867	0.7	Valid
	PU 4	0.831	0.7	Valid
	PU 5	0.793	0.7	Valid

Based on the second-stage convergent validity test, as presented in Table 2, all remaining indicators met the established criteria, with loading factor values greater than 0.7. This indicates that each indicator used in the study has a strong correlation with its respective construct and can be considered valid as a representation of the latent variable. The research constructs have met the convergent validity assumptions, meaning that the measurement instruments are capable of consistently and accurately reflecting the research variables. Theoretically, convergent validity is determined by the correlation between the indicator scores and their respective construct scores, where a loading factor > 0.7 is used as the minimum threshold for the feasibility of indicators within the measurement model.

Average Variance Extracted (AVE) Test

Furthermore, convergent validity was also assessed using AVE for each research variable. The AVE value represents the proportion of indicator variance that can be explained by the latent construct relative to the variance caused by measurement error. The main criterion for evaluating AVE is that it must be greater than 0.5 to be considered as meeting the convergent validity requirement. The results of AVE test are presented in the following table:

Table 3. The Result of Average Variance Extracted (AVE) Test

	Average Variance Extracted (AVE)	Level of *Average Variance Extracted*	Explanation
ATU	0.663	0,5	Valid
AU	0.574	0,5	Valid
BITU	0.597	0,5	Valid
CSE	0.721	0,5	Valid
PEOU	0.758	0,5	Valid
PU	0.662	0,5	Valid

The table above shows that the AVE values of all research variables are greater than 0.5. This indicates that the research variables meet AVE criteria, where an AVE > 0.5 signifies that the variable can be considered a good research construct. The AVE value for the CSE variable is 0.721, while the AVE values for ATU and AU are 0.663 and 0.574, respectively. The BITU and PEOU variables have

AVE values of 0.594 and 0.758, respectively. Finally, the AVE value for PU is 0.662. Thus, all constructs in the model meet the convergent validity criteria based on AVE, as each construct explains more than 50% of the variance in its indicators.

Hypothesis Test

The final stage in analyzing the influence of variables in the structural model testing is to conduct the research hypothesis testing, which represents the relationships between variables. The analysis is performed using the bootstrapping process, which produces significance values among variables. To determine whether a hypothesis is accepted or rejected, the significance values, including coefficients, t-statistics, and p-values, are examined. In this study, a 5% significance level is used to test the hypotheses. At the 5% significance level, a hypothesis is accepted if the t-statistic is greater than the critical t-value of 1.66. The following table presents the bootstrapping output results:

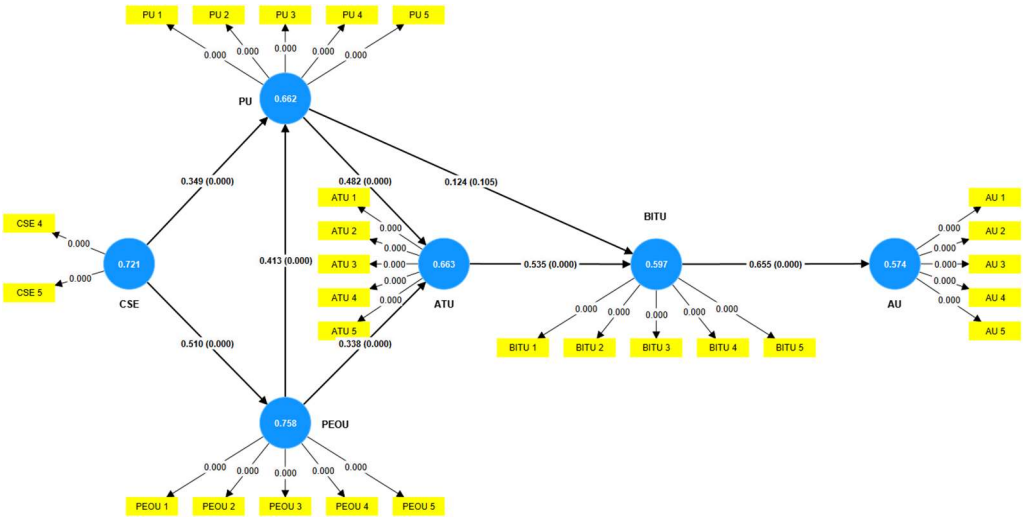

Figure 3. The Result of Hypothesis Test

The figure above shows the bootstrapping output results using SmartPLS, which indicate whether the six hypotheses in this study are accepted or rejected. The results of bootstrapping may vary because the method relies on resampling the original data. To obtain more stable bootstrapping results, a larger number of resamples can be used; however, this will require more processing time. Based on the bootstrapping results, five hypotheses were accepted, and one hypothesis was rejected. A more detailed explanation can be found in Table 4 below.

Table 4. The Result of Path Coefiicient

Hypothesis	T-tabel	T-Statistics	P.Value	Explanation
CSE-> PEOU	1.96	9.556	0.000	Accepted
CSE-> PU	1.96	5.912	0.000	Accepted
ATU -> BITU	1.96	9.095	0.000	Accepted
BITU -> AU	1.96	16.280	0.000	Accepted
PEOU -> ATU	1.96	5.108	0.000	Accepted
PEOU-> PU	1.96	7.313	0.000	Accepted

Hypothesis	T-tabel	T-Statistics	P.Value	Explanation
PU->ATU	1.96	8.183	0.000	Accepted
PU->BITU	1.96	1.623	0.105	Rejected

Based on the data presented in the table above, the hypothesis testing results were obtained using the bootstrapping method, assessing the significance of the relationships between variables through T-statistics. A hypothesis is considered significant or accepted if the T-statistic > T-table and the P-value < 0.05. The P-value represents the probability observed in the statistical test. In this study, out of the eight proposed hypotheses, seven were accepted, demonstrating the robustness of the findings, while one was rejected. Specifically, the T-statistics of seven hypotheses exceeded 1.96 with P-values below 0.05, confirming their significance, whereas one hypothesis had a T-statistic below 1.96 with a P-value greater than 0.05, leading to its rejection.

The analysis results indicate that Computer Self-Efficacy (CSE) has a positive and significant effect on Perceived Usefulness (PU), with an original sample value of 0.349, T-statistic of 5.912, and P-value of 0.000. Highlighting CSE's influence can help the audience feel reassured about the importance of confidence in using technology. Furthermore, CSE also positively and significantly affects Perceived Ease of Use (PEOU), with an original sample of 0.510, T-statistic of 9.556, and P-value of 0.000. The relationship between PEOU and PU shows a positive and significant effect, with an original sample of 0.413, T-statistic of 7.313, and P-value of 0.000. Additionally, PU has a positive and significant effect on Attitude Toward Using (ATU), with an original sample of 0.482, T-statistic of 8.183, and P-value of 0.000.

The relationship between PEOU and ATU also demonstrates a positive and significant effect, with an original sample of 0.338, T-statistic of 5.018, and P-value of 0.000. Emphasizing this connection can help the audience feel assured about the role of attitude in technology acceptance. However, the relationship between PU and Behavioral Intention to Use (BITU) was not significant, indicated by an original sample of 0.124, T-statistic of 1.623, and P-value of 0.105. Subsequently, ATU positively and significantly affects BITU, with an original sample of 0.535, T-statistic of 9.095, and P-value of 0.000. Finally, BITU has a positive and significant effect on Actual Use (AU), with an original sample of 0.655, T-statistic of 16.280, and P-value of 0.000.

Overall, most relationships in TAM tested show significant effect, and underscores the importance of these factors in technology acceptance. The findings suggest that Computer Self-Efficacy (CSE) significantly influences perceptions of ease of use (PEOU) and usefulness (PU). These perceptions, in turn, shape a positive attitude toward using technology (ATU), which strongly predicts the intention to use (BITU). This intention then leads to actual use (AU), highlighting that students' confidence in using technology is a key driver in technology adoption within educational settings.

Discussion

The results of this study indicate that CSE has a significant effect on both PU and PEOU. Highlighting students' confidence in using technology emphasizes its role in shaping perceptions of AI-based technologies' usefulness and ease of use. Students with strong technological skills and self-confidence tend to better understand how the technology functions and appreciate the benefits it provides in the learning process. These findings highlighted that fundamental competencies in ICT serve as an essential foundation for the acceptance of AI-based technologies among Islamic Education students at PTKIN in Central Java. The use of AI in education has become an important issue with the publication of guidelines in higher education. This step represents a significant policy for both students and lecturers within academic environments. The use of Generative AI (GenAI) can be classified into several purposes. First, its use by students for learning can leverage GenAI to acquire knowledge more quickly and efficiently, allowing their academic tasks to be completed more optimally. Second, its use by lecturers in the learning process can enhance effectiveness, efficiency, and the overall quality of higher education. Third, its use in higher education administration enables institutions to be managed more efficiently and effectively.

Furthermore, this study indicates that PEOU significantly affects PU, demonstrating that a user-friendly interface, simple navigation, and minimal technical barriers enhance students' confidence that translation technology effectively supports their learning to comprehend English-language religious texts. This finding aligns with the TAM framework, which emphasizes that technologies perceived as easier to use lead to higher perceived usefulness. In the context of PTKIN learning, the ease of using translation technology allows students to focus more on understanding content rather than struggling with operational difficulties. Therefore, enhancing the ease-of-use aspect can serve as a strategic approach to strengthen the adoption of translation technology in supporting academic literacy among Islamic Education students. This result is consistent with the classic study by Baiquni et al. (2025) and Enggal et al. (2026), which asserts that perceived ease is a primary trigger that activates the perceived usefulness of a system. Prior research by Aisyah et al. (2025) and Kamalia (2023) also proved that when the cognitive load of operating a technology decreases, users automatically perceive a greater functional value from the tool. Additionally, in the realm of foreign language learning, research by digital humanities experts shows that intuitive applications are proven to accelerate students' transition from merely reading text to deeply understanding the essence of academic content.

The causal relationship between perceived ease of use (PEOU) and perceived usefulness (PU) is triggered by the characteristics of Islamic Education students, who often face a double barrier: linguistic limitations combined with technology anxiety. When AI platforms provide subtle navigation and are free of technical obstacles, it triggers a positive psychological effect in the form of reduced mental resistance among students toward foreign literature. This operational ease acts as a stimulus that directly reduces time wasted on technicalities of translation,

thereby allowing students to divert their cognitive energy toward absorbing high-value religious substance. Consequently, this efficiency of time and energy forms a causal conclusion in students' minds that the technology is highly useful for their academic success.

Ease of use also increases students' confidence that technology can assist their learning process. Moreover, PU and PEOU are proven to significantly influence ATU, indicating that students' perceptions of usefulness and ease of use contribute to the formation of positive attitudes toward utilizing technology in learning. When students experience tangible benefits and find the technology easy to use, their attitude toward leveraging technology in an educational context tends to improve. Enhancing feature quality, accessibility, and clarity of technological functions can strategically drive student acceptance of technology in the learning process. This empirical finding reinforces the validity of the integrated TAM model, which states that an individual's affective response or attitude (ATU) is formed simultaneously by cognitive evaluations of the tool's usefulness and ease. A review of the literature from various e-learning adoption studies (Alenezi, 2023; Arif et al., 2025; Fraillon, 2023) consistently showed that instrumental satisfaction with technology performance is the primary foundation for the emergence of an emotional interest to continue using it. Furthermore, several case studies at religion-based higher education institutions (Habes et al., 2023; Rodríguez-Fuentes et al., 2025; Shatila et al., 2024) confirmed that an open attitude toward instructional modernization emerges organically when students perceive real efficiencies facilitated by digital systems.

The formation of a positive attitude (ATU) did not occur in a vacuum; rather, it is the result of students' rational calculations regarding the ratio between effort and outcome. The English language barrier, which has long been a daunting specter for Islamic Education students, collapses instantly when the real usefulness of AI meets ease of access. The frustration that usually accompanies the process of reading Western literature transforms into a satisfying and empowering learning experience. This emotional transformation from fear to a sense of capability causally drives students to enthusiastically embrace technology, triggering a paradigm shift from conventional learning methods toward an adaptive digital ecosystem.

However, this study also found that PU does not have a significant influence on BITU. This finding indicates that even though students perceive the technology as useful, this perception alone does not directly translate into an intention to use it. This condition may arise due to several factors, such as a lack of urgent need for the technology, limited facilities, dependence on instructor guidance, or a lack of habit in independently accessing AI technology for English text translation. This highlights an important insight: the perception of benefits alone is insufficient to drive the intention to use technology among Islamic Education students at PTKIN in Central Java. This theoretical anomaly apparently aligns with several deviations in earlier TAM studies, where usefulness does not necessarily trigger intention if there is strong intervention from external or cultural factors. Research by Alshahrani & Qureshi (2024); Do et al. (2023) and Machmudah et al. (2026) shows

that in a collective and instructional academic environment, an individual's intention is often hindered by the absence of a formal mandate or curricular push from the faculty. Additionally, studies in the context of developing countries frequently report that recognition of a technology's benefits will remain passive and fail to manifest into actual intention if it is not accompanied by equitable digital infrastructure readiness.

The non-significant influence of usefulness on behavioral intention is caused by a gap between cognitive awareness and practical urgency in the field. Islamic Education students at PTKIN Central Java theoretically understand that AI is highly beneficial, yet causally they do not feel compelled to use it because the daily academic climate has not fully integrated international literature as an absolute, mandatory reference. A learning culture that remains centered on Indonesian or Arabic textbooks renders the need for AI English translators optional rather than a primary necessity. The absence of structural pressure or urgent assignment demands from lecturers breaks this causal chain, causing the perception of usefulness to stop at a passive evaluation without generating an impulse for behavioral intention.

On the other hand, the research results show that ATU has a significant influence on BITU, indicating that a positive attitude toward technology can inspire students and shape their willingness to utilize it. Furthermore, BITU is proven to significantly affect AU, implying that students' intention to use technology contributes to its actual utilization in learning activities. Overall, technology acceptance among Islamic Education students is influenced by various factors, including self-confidence in using technology, perceived ease of use, and a positive attitude toward its utilization. This relational cycle is highly consistent with the core tenet of the Theory of Reasoned Action (TRA), which positions intention as the most accurate and proximal predictor of actual human behaviour (Agustina et al., 2023; Alam et al., 2025; Siyam et al., 2025; Wu, 2024). Many prior studies in educational technology confirm that affection or liking (ATU) is the strongest psychological fuel that converts intention into actual action in the classroom (Ayuba et al., 2025; Huang et al., 2024; Hussam & Liyawu, 2025). Empirical support from contemporary digital literacy research also indicates that students with a directed intention tend to be more persistent in exploring advanced technology features to complete their academic tasks independently.

Causally, the bridge connecting attitude (ATU), intention (BITU), and actual use (AU) is driven by the consistency of students' psychological behavior. When a Islamic Education student has developed a liking and trust toward AI, this affective attraction mechanically triggers an internal commitment or a strong intention to allocate learning time using the tool. This crystallized intention then acts as a behavioral driver that compels the student to take concrete action, such as downloading an application or opening an AI website when facing an English reading assignment. Thus, the realization of actual use is a direct causal consequence of mental readiness and a settled intention that matured in the preceding phases.

The stronger a student's intention, the more likely that student will actively use AI to translate English literature in their daily learning activities. Collectively, the research model indicates that technology acceptance among Islamic Education students is heavily influenced by computer self-efficacy, perceived ease of use, and a positive attitude toward learning media. However, perceived usefulness alone is insufficient to drive technology adoption without the support of a favorable attitude. This comprehensive conclusion confirms the modified, integrated TAM model, which states that successful technology adoption requires a holistic approach encompassing technical, psychological, and functional capacities. Previous studies in the realm of Computer Self-Efficacy assert that belief in one's capability to interact with computers is a vital catalyst that accelerates the effectiveness of all TAM variables (Adhinugraha et al., 2024; Id et al., 2023; Yundianto et al., 2023). In addition, global literature regarding technology integration in religious higher education environments concludes that adoption failures often occur not because of flaws in the technology itself, but rather due to the neglect of the users' attitudinal readiness and self-confidence (Er et al., 2023; Othman et al., 2024; Thien & Liu, 2024).

The actual adoption of AI in translating English literature among Islamic Education students is the result of an interactive system of cause and effect. Computer self-efficacy acts as the upstream or the initial capital; students who are confident in their digital skills will not feel anxious when facing new technology, which in turn leads them to perceive the operational process of AI as easy. This ease and usefulness running hand-in-hand generate emotional satisfaction that gives rise to a positive attitude. This positive attitude serves as the primary engine that generates intention, ultimately culminating in actual use (AU). This causal chain proves that without psychological readiness in the form of self-efficacy and a positive attitude, the functional sophistication of AI will remain barren and will never manifest into sustainable usage behavior.

An important contribution of this study lies in advancing the understanding of technology acceptance in education, particularly regarding the use of AI to assist Islamic Education students in comprehending English-language Islamic educational literature. Practically, these findings can serve as a foundation for higher education institutions to enhance students' digital literacy through training in technology use and the integration of AI into learning processes. As actionable steps, educational institutions may develop AI-assisted learning support programs, provide clear guidelines for utilizing AI in reading English-language literature, and encourage instructors to employ AI as a pedagogical tool to improve students' academic understanding.

CONCLUSION

The primary factors influencing Islamic Education students' acceptance of AI technology in understanding English-language Islamic education literature are CSE and perceived ease of use, which significantly shape students' attitudes toward technology. The findings indicate that CSE plays a crucial role in shaping students' perceptions of the usefulness and ease of use of AI, which in turn

influences their attitude toward utilizing the technology. Moreover, a positive attitude toward AI encourages behavioral intention to use it, ultimately affecting the actual use of AI in the learning process. This demonstrates that psychological factors and user perceptions are key determinants in the effective utilization of learning technologies. The study's strength lies in its analytical model, which effectively explains the relationships among variables in AI technology acceptance within the learning context. However, the study is limited by its sample scope, which is restricted to Islamic Education students in a specific region, such as [region or country], meaning the findings cannot yet be fully generalized to broader educational contexts. Therefore, future research is recommended to expand the sample size and diversity, incorporate additional variables such as social factors or prior technology experience, and explore the utilization of AI in other academic activities more comprehensively.

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