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Muslim students' acceptance of artificial intelligence in Islamic religious education: an extended TAM approach

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Abstract
The emergence of artificial intelligence (AI) in education and religion in today's world has presented various challenges, such as plagiarisms, the credibility of AI and, its acceptance by students. This study uses an extended Technology Acceptance Model (TAM) framework to analyse Muslim students' perceptions towards the use of artificial intelligence (AI) in learning Islamic education in Indonesia. The data of this study consisted of 224 Muslim student respondents collected from 12 universities through random sampling technique assisted by the Indonesian Islamic Higher Education Lecturer Association (ADPISI) and analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM) approach. The main findings indicate that Perceived Ease of Use (PEOU) has a significant effect on Perceived Usefulness (PU). Meanwhile, PU has a direct influence on Attitude Toward Using AI (AT) and on Behavioural Intention to Use AI (BI). In addition, AT is also an important determinant in shaping BI. These results prove that the easiness and usefulness that students get from artificial intelligence (AI) technology in learning Islam are the main factors in shaping students' positive attitudes and intentions to use AI in Islamic religious education. Although the level of AI use in the context of religious learning is still limited, students show positive attitudes. that even in Islamic religious education, Muslim students tend to use artificial intelligence (AI) in their learning. The implications of these findings encourage the development of AI systems that are adaptive to Islamic values and ethics.

Keywords Artificial intelligence, Higher education, Muslim students, Extended TAM, Religious education

1 Introduction

The increasing use of AI technologies in student life is shaping new learning experiences. Generative AI technology tools such as ChatGPT, Copilot, Meta AI, etc. support students in developing ideas and writing papers that have the potential to improve the quality of their academic work. This is happening in almost all countries [1–4]. Students' acceptance and perception of its usefulness in the learning process is highly influential in determining effective integration efforts into the higher education environment to improve the pedagogical process outcomes [5].

Students feel that AI offers personalised learning while providing real-time feedback and can be tailored to individual learning pace. With AI, students can also hone their 21st century skills [6]. In Islamic education, the application of AI poses distinctive moral and theological questions. AI is being utilised in religious matters and religious activities as advances in AI technology make it available [7–9]. Adaptive learning, predictive analytics, natural language processing and gamification can be well supported and enhanced by AI. Moreover, also in response to the digitalisation age, AI can speed up and ease the difficulty of learning, personalized recommendations, and forecast [10, 11].

Perception of technology based on ease, values and relevance to need can affect the paradigm [12]. Similarly, the students' views on AI technology are reported to have impacted the manner in which the technology is integrated in the learning that is in the academic space. In the area of Islamic religious education, while presenting Islamic values and ethics also influence Muslim students attitude towards technology [13, 14]. Despite the popularity of AI in education, academia, and religion, there is still very little research conducted to investigate this issue. The research by Hayati & Sayekti (2024) [12] related to this issue was only conducted at the UIN Sumatera campus, while the research by Achruh et al. (2024) highlighted the use of AI and traditional teaching methods [15], and Saihi et al. (2024) questioned the reliability, bias, and accuracy of AI [16].

These studies have not comprehensively discussed the acceptance and use of AI by Muslim students in higher education, especially in the context of Islamic education or Islamic religious learning. This gap motivated a study on the perception and use of AI technology by Muslim students in learning Islam. Based on the Technology Acceptance Model (TAM) theory, we explored how Muslim students in higher education model the use and acceptance of AI technology in learning Islamic religious materials. This research also seeks to examine their perceived usefulness and convenience in learning about Islam.

This study aims to answer the following research questions:

(a) What is the Muslim students' perception of the use of AI in learning Islam, and does this perception influence their intention to use AI in learning Islam?
(b) Whether the value of students' perception of the machine (AI) is used directly with learning Islam?
(c) To what extent do students feeling of AI usefulness in learning Islam impact on students' attitude towards and intention of using AI in learning Islam?

The purpose of this research is to investigate students' acceptance of artificial intelligence (AI) and the variables that influence the intention and use of AI technology in Islamic learning by applying the Technology Acceptance Model (TAM) framework, which has been tested to investigate technology adoption or integration. The research applies an extended TAM model, which is a technology acceptance model that argues that attitudes (AT) towards technology are determined by perceived ease of use (PEOU) and that perceived usefulness (PU) influences their intention (BI) to use it.

1.1 Technology acceptance model (TAM) of AI in religious education

The technology acceptance model (TAM) considers technology from a sociological perspective. Within the scope of this research, it means the use of AI technology by a Muslim student for learning purposes. This model has 2 key components: perceived usefulness (PU), which is evaluation during a learning process, and perceived ease of use (PEOU) [17, 18]. The theory that perceived ease of use and perceived usefulness are key predictors of technology acceptance aligns with the need to track how AI helps achieve educational goals in the Islamic context.

These constructs are important in determining how an individual may accept and utilise the benefits of a new technology. It is assumed that these two constructs impact attitudes towards using AI and also impact intentions and actual behaviour. In the study, the use of the theory was utilised to observe the acceptance of AI technology in education. It was also applied to web-based learning systems and the use of virtual media to enhance teaching and learning effectiveness [17].

Usman et al. examined the development of Islamic learning, including technology integration, in three State Islamic Universities in Indonesia. Using a qualitative approach, the study saw dynamic development and transformation [19]. Syahrizal et al. examined the use of AI in the development of multimedia teaching materials for Islamic religious education at the senior high school (SMA) level in Indonesia. The interactive multimedia teaching materials were successfully developed by utilising AI technology [20].

Regarding students' perceptions of the use of AI in general, Agung et al. found that students generally had a positive view of AI writing aids. Students recognised its benefits in grammar checking, plagiarism detection, language translation, and essay parsing, but some students were concerned about its adverse effects [21]. Hayati & Sayekti's study of students at UIN Sumatera campus showed that Muslim students generally showed a positive attitude towards AI technology. They tend to see AI as a tool that can be integrated into education and daily life [12].

In general, students' perceptions of the use of AI in learning Islam in Indonesia are positive, but there has been no specific research on the use of AI in learning Islam or Islamic religious education. Research by Achruh et al. mentioned a potential tension between the use of personalised AI and traditional methods that are teacher-centred and emphasise memorisation [15]. The use of AI is seen as the technology is used to improve the user's performance, effectiveness, or productivity. Perceived usefulness is measured by the benefits of AI in supporting students' learning process, such as helping to understand lecture material or fulfil academic tasks, navigation, and daily activities. However, Saihi et al. stated that there are challenges related to trust, response bias, privacy, and information accuracy that are major problems [16], although recently this has begun to be unproven due to the perceived benefits and relatively acceptable content [22, 23].

1.2 Perceived ease of use (PEOU) of AI in Islamic education

The Perceived Ease of Use (PEOU) of technology in Islamic education is an important area to explore as traditional teaching methods have long been utilised in it. Popenici and Kerr point out the wide-ranging implications of AI in education and argue that it is driving a rethinking of traditional pedagogical roles as well as changing the way users perceive the ease of use of technology [24]. Liu et al. emphasised that AI technology greatly facilitates educators in optimising content design and facilitating the learning process and ultimately leads to a more comprehensive evaluation of learning outcomes [25]. Fandir through his research also concluded on the importance of using innovative digital platforms in Islamic education to improve the perspective of convenience, especially during the past pandemic [26].

The advent of AI brings opportunities and challenges that impact the perception of the usability of the technology. One of the most important parts to consider under the umbrella of PEOU is the understanding of AI's expected impact on facilitating teaching and learning. Technology impacts the fulfillment of academic and even religious obligations. Efrizal notes that through ease of adaptation to personal learning styles and provision of dynamic content, AI technology fosters participatory and inclusive atmosphere of learning [27]. Firnando's findings also indicate that in the educational sphere of the Islamic world, the role of AI is on the rise and its potential to provide personalized education at affordable rates is emerging [28].

Xiong et al. argue, PEOU towards AI is likely to increase with confidence in the technology due to the clarity, reliability and trustworthiness of its application. In their view, AI has the ability to foster an environment for individualised learning which could motivate learners' participation and willingness [29]. Hakim in his study of the systematic challenges and opportunities of AI in Islamic studies pointed out that user perceptions are largely reactive to the interface of the technology and the educational content [30].

Research by Abubakari and Priyanto's on technology acceptance in educational institutions indicates that different religious perspectives have an effect on technology acceptance [31]. According to the study, as long as technology is applied based on religious teachings, PEOU among educators and students will increase. These findings highlight that culturally relevant framing of AI solutions can greatly influence their perceived usefulness in an educational context.

Furthermore, the impediments discovered by Sholeh also suggests that better supportive infrastructure and training programs must be developed in order to enhance PEOU towards the implementation of technology into the Islamic education system [32]. Research by Sholeh et al. also defined that the AI can be integrated into religion education and it can give better understanding between concept, but in religion education the AI successful application are the culture content context, ethic issue and the education responsibility [33]. Utami et al. also stated that Indonesian students' perceptions of the ease of use of AI technology in academic writing classes were positive, but the tools could not fully replace the teacher's role [34]. In other words, PEOU may be high, but acceptance may depend on religious frameworks, ethical issues, or culture.

1.3 Perceived usefulness (PU) of AI in Islamic education

Perceived usefulness (PU) is the extent to which users believe that the technology can provide benefits in the form of the best performance for its users. In this study, PU is the usefulness or best performance provided by AI in the process of learning Islam. One important aspect of AI usability lies in its ability to provide a personalised learning experience. Efrizal in his research explains how AI can adapt learning interactions based on individual weaknesses and strengths regarding language acquisition while underlining its function in enhancing student participation and the teaching of Islamic teachings [27].

According to the research, artificial intelligence (AI) has the potential to enhance education, but its application needs to be properly controlled to preserve the integrity of Islamic teachings. Concerns should also be raised about the administrative effects of AI in learning environments. According to research by Alotaibi and Alshehri, integrating AI into higher education can improve overall efficiency by streamlining administrative procedures, freeing up teachers to concentrate more on instruction rather than paperwork [35].

AI for analysis of religious texts Alkhouri explained how AI is employed in analysis of religious texts. "AI helps us understand much more about what it was that took place, culturally, in its day, not just historically," he said, and understanding historical and cultural settings is integral to properly interpreting and teaching religious traditions. AI can not only be used in textual analysis but can also optimize the research workflow and the way of working in general in religious studies and other humanities to boost the productivity of academics [36]. Lima et al. utilized AI for automating the generation of context-based Bible quotes and generating sermons. Such tech frees up time and lets scholars concentrate on (the more difficult) issues and interpretations of texts that take real engagement and critical assessment [37].

Tsuria and Tsuria reported that, by using sentiment-analysis tools, there is an exposure to diverse viewpoints across different religious affiliation, and an understanding to engage with nuanced religious issues more deeply [38]. However useful and beneficial it may be, critics claim that dependence on AI could supplant reflective, critical thinking and diminish the level of personal engagement with religious texts. For Andriansyah, as AI technologies, such as ChatGPT continue to advance, scholars must remain vigilant to investigating the implications of AI-generated content to religious talk and pedagogical practices [39].

Although AI has the potential to help further understanding and productivity for religious studies, it also raises concerns ethical and practical issues. To strike a balance on the utilization of AI in Islamic religious education and promote a sense of caution, the present paper focusses on the perceptions of Muslim learners regarding the use and ease of utilization of AI in the context of Islamic religious education (IRE).

Based on the theory described above and findings from previous research, the relationship between each variable in this research model is designed in a model that has five hypotheses as follows:

(a) H1: The Perceived Ease of Use, PEOU, has a positive impact on Perceived Usefulness, PU.
(b) H2: The Perceived Ease of Use, PEOU, has a positive impact on the Attitude Toward Using, AT.
(c) H3: The Perceived Usefulness, PU, has a positive impact on the Attitude Toward Using, AT.
(d) H4: The Perceived Usefulness, PU, has a positive impact on the Behavioural Intention, BI.
(e) H5: The Attitude Toward Using, AT, has a positive influence on the Behavioural Intention, BI.

The answers to these hypotheses are expected to explain and understand the relationship between variables and how Muslim students interact with AI and the extent to which AI helps them in learning Islam. These answers are expected to become the basis for how AI is adopted for Islamic religious education at the Islamic higher education level.

2 Methodology

In this study, we employed survey research as a quantitative methodology and implemented it to collect information related to the perception and the use of AI in relation to attending the course of Islamic Religion/Islamic religious education for Muslim students.

The population of this study was Muslim students attending Islamic religion or Islamic religious education courses in Indonesian universities, specifically public universities affiliated to the Ministry of Education of the Republic of Indonesia, as opposed to religious universities affiliated to the Ministry of Religious Affairs of the Republic of Indonesia. The number of respondents was 224 consisting of 91 males (40.6%) and 133 (59.4%) females from 12 universities spread across Indonesia. After explaining the purpose of the research in the questionnaire, the researchers obtained written informed consent from the participants after they provided their answers. They gave it voluntarily with the assurance that the confidentiality of the research data would be maintained.

The sampling was conducted using random sampling technique through questionnaires distributed online through the media WhatsApp groups of Islamic Religious Education classes assisted by lecturers gathered in the Association of Indonesian Islamic Religious Education Lecturers (ADPISI) to their students who take Islamic religion or Islamic religious education courses on their respective campuses.

The questionnaire was designed to measure Muslim students' perceptions of AI in the context of Islamic religious education, which is based on the technology acceptance model (TAM) theory which includes the level of utilisation of AI in learning Islamic religious education; factors that influence the use of AI in the course. The questionnaire was developed using a Likert scale of 1–5 to measure the level of agreement or disagreement of respondents to the statements in the questionnaire. The instrument has been validated by three experts in the field of educational technology and Islamic education, then tested on students to assess the clarity of language and question structure.

The time of data collection was conducted for approximately 2 months (between February and March 2025). Of the respondents who have used AI, not all of them have used AI in Islamic education lectures or in Islamic learning. Out of 224 respondents, only 1 (0.45%) answered that they very often used AI in learning Islam; 36 (16.13%) answered often; 98 (43.90%) answered sometimes; 65 (29.12%) answered rarely; and 24 (10.75%) answered never. The next section of the questionnaire asked respondents to answer items related to attitude towards AI, perceived benefits and usefulness of AI, perceived ease of use of AI, and intention to use AI. All of these were in the context of Islamic learning.

2.1 Data analysis

Data analysis included descriptive statistical analysis to describe the Islamic religious affiliation characteristics of the respondents, and the types of generative AI used as well as to see how Muslim students' perspectives on the use of AI in learning Islam. This study also used a correlation test between Likert scale variables. Data were analysed using SmartPLS v.4.0.9.9 statistical software for Structural Equation Modelling (SEM) analysis with the Partial Least Squares (PLS) approach. Some researchers find that PLS-SEM is very helpful for predicting significant factors or selecting important aspects [40, 41].

Researchers analyse data and test hypotheses, starting with descriptive statistics and reliability analysis to assess data quality and measurement scales. The steps in PLS-SEM analysis involve assessing data quality and validity, estimating Path Coefficients to test the hypothesised relationships and interpreting the results to infer the relationships between the constructs. The researcher considered Cronbach's Alpha and Composite Reliability (CR) for testing the validity and reliability of each construct to evaluate the quality of the research instrument. Convergent validity was also examined through the Average Variance Extracted (AVE) value. Researchers assess good convergent validity if the AVE value exceeds 0.50, which means that the construct can explain more than half of the variance of its indicators [42–44]. In this study, all constructs show an AVE value above 0.50, which supports the assumption that each construct has sufficient convergent validity.

Next, the researcher conducted SEM analysis to test the hypothesis of the relationship between attitude towards AI, perceived usefulness, ease of use, and intention to use by conducting Hypothesis Testing and Path Coefficient Estimation between attitude, perceived usefulness, intention to use, and ease of use. These coefficients indicate the strength and direction of the relationship between the variables. Hypothesis testing involves significance testing (p-value) with 0.05 as the level of significance and t-test to test the significance of the strength and direction of the relationship between the latent variables [45–47]. The results of the data analysis were interpreted in light of the findings. Figure 1 summarises the methodology used in this study.

3 Results and discussion

3.1 Student attitudes towards AI

More than five respondents' religious affiliations were entered, and more than seven different AIs were used. ChatGPT was the most frequently used AI, followed by Gemini, Meta AI and others. Descriptive analysis of the construct of student attitudes towards AI shows a mean value of about 3.5 on a scale of 1 to 5, which means that the distribution of answers is in the middle of the scale (neutral) tends to be positive and the standard deviation is about 0.8, which indicates that the variation in answers is not too high, meaning that most respondents are around the middle value. Meanwhile, the skewness value shows that the distribution of answers is almost symmetrical and does not lean extreme to negative or positive. The kurtosis value shows that the data tends to be normal

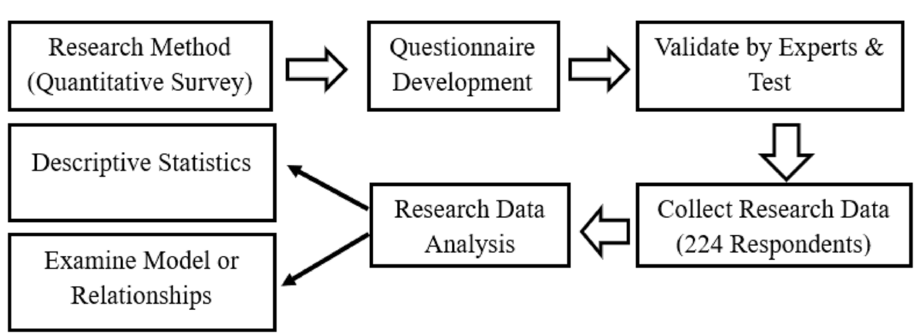

Fig. 1 Research procedure flowchart

without a high spike in one value. Skewness values between − 0 and 0.0 are considered excellent, while values out of −2 and + 2 indicate substantial abnormalities. Hair et al. explain that kurtosis values greater than + 2 indicate a distribution that is too peaked, while values less than − 2 indicate a distribution that is too flat [48]. The interpretation of the above results shows that Muslim students' views on the use of AI in learning Islam are in the neutral to moderately positive range. Table 1 shows a mean of 3.294 on a scale of 1 to 5 with a standard deviation of 0.553, meaning that the majority of respondents were neutral with a tendency towards agreement. The relatively low standard deviation value (0.553) indicates that the answers given are consistent.

These results seem slightly different from the results of previous studies that show students' perceptions of AI in higher education which show positive perceptions [12, 15, 16, 21]. In other words, Muslim students generally do not reject the use of AI in Islamic learning, and some even show interest and positive views, although the interest is not yet strong. It is possible that this somewhat different result is because the courses or materials studied are religious or Islamic materials that tend to be in the form of doctrine and faith, not because of the convenience or usefulness factors of AI technology. This finding can then be the basis for further analysis of the relationship model between student attitudes and other factors.

3.2 Measurement model assessment

Structural Equation Modelling (SEM) evaluates measurement models using various fit indices and statistical tests [49, 50]. Evaluation of the measurement model in this study involves assessing the validity and reliability of the latent constructs in the PLS-SEM model. Reliability is measured using Cronbach's alpha and Composite Reliability, with values above 0.70 to be considered adequate [51, 52]. Validity assessment includes content, criterion-related, and construct validity [53]. Table 2 shows the resulting model in the form of an evaluation of indicators for the constructs of Behavioural Intention (BI), Perceived Ease of Use (PEOU), Perceived Usefulness (PU), and Attitude Toward AI (AT). This assessment includes three main aspects: indicator reliability (outer loading), construct reliability (CR), and convergent validity (AVE).

Based on the analysis results shown in Table 2. it can be explained that most of the indicators have factor loadings above the recommended threshold, which is 0.7. Although PEOU2, PEOU3, and PU4 have loading factors of less than 0.7, with an AVE greater than 0.5 and considering the importance of these indicators in constructing variables, researchers still retain them. These values indicate that these indicators have a strong contribution in measuring the construct. Values of loading factors that are less than 0.7 indicate potential concerns regarding the validity and strength of their contribution to the measurement model because loading factors reflect the extent to which an item correlates with the corresponding latent construct. In the sense that higher values indicate a stronger and more reliable relationship. In social science research, a loading

Table 1 Descriptive statistics results

Name	Mean	Median	Scale min	Scale max	Standard deviation	Excess kurtosis	Skewness
AT1	3.482	4,000	1.000	5.000	0.796	−0.193	−0.289
AT2	3.121	3.000	1.000	5.000	0.778	−0.461	0.072
AT3	3.094	3.000	1.000	5.000	0.810	−0.390	−0.021
AT4	3.482	3.000	1.000	5.000	0.802	−0.195	−0.046

Table 2 Measurement model results

Construct	Item	Loading	Cronbach's Alpha	Composite Reliability (CR)	AVE
Attitude Toward AI	AT1	0.774	0.820	0.881	0.650
	AT2	0.860			
	AT3	0.838			
	AT4	0.749			
Perceived Ease of Use	PEOU1	0.893	0.663	0.770	0.535
	PEOU2	0.582			
	PEOU3	0.686			
Perceived Usefulness	PU1	0.801	0.761	0.893	0.737
	PU2	0.828			
	PU3	0.768			
	PU4	0.646			
Behavioural Intention	BI1	0.874	0.822	0.903	0.756
	BI2	0.908			
	BI3	0.788			

Table 3 Fornell-Larcker criterion results

	AT	BI	PEOU	PU
Attitude Toward	**0.806**			
Behavioural Intention	0.633	**0.858**		
Perceived Ease of Use	0.630	0.471	**0.732**	
Perceived Usefulness	0.718	0.607	0.668	**0.764**

value ≥ 0.7 is generally acceptable as it indicates that the construct accounts for at least 50% of the variance in the indicator [40]. The decision to retain or eliminate these lower loading items depends on the extent to which they are theoretically justified or empirically valuable. In addition, loading factors ≥ 0.4 to 0.6 are acceptable in exploratory research [48, 54]. Based on this explanation, the researchers retained the items by considering their urgency and considering the impact of their inclusion and exclusion on the integrity and interpretability of the construct.

The Average Variance Extracted (AVE) value indicates the value of convergent validity. AVE is an important component of construct validity. AVE is calculated as the average of the squared charges for all items associated with a construct. The AVE value > 0.5 in this study indicates that the construct can explain more than half of the variance in its indicators. As seen in Table 2, all constructs show AVE values that exceed 0.5, thus meeting the criteria for convergent validity. Meanwhile, the Cronbach's Alpha and Composite Reliability (CR) values for all constructs confirm the reliability of the internal consistency of the measurement model. These results collectively support the conclusion that apart from a few items that have lower loadings, the overall measurement model is reliable and valid and worthy of proceeding with the structural model evaluation.

In summary, the internal reliability of the data was met and demonstrated consistency between items within the same construct. Convergent validity was also achieved indicating that the indicators indeed reflect the intended construct. So, overall, the constructs in the model can be said to have adequate measurement quality and can proceed to structural model analysis (SEM).

Evaluation of the discriminant validity of the constructs in the model using the Fornell-Larcker Criterion approach can be seen in Table 3. To establish discriminant validity, the square root of the AVE of each construct must be greater than the highest correlation with other constructs. Discriminant validity serves to ensure that a construct is empirically different from other constructs in the model and the indicators in a construct reflect the construct more than other constructs [48].

The Fornell-Larcker results in Table 3 show that the square root value of the AVE (Average Variance Extracted) for each construct (shown in bold diagonal values) is greater than the correlation value between other constructs in the same column/row. This construct meets the Fornell-Larcker discriminant validity criteria.

These results indicate that these items are strongly related to the BI construct and make a significant contribution to its measurement. In the Attitude Toward (AT) construct, four items have high loading factors, ranging from 0.749 to 0.860. This also shows that the items are very well related to the AT construct.

The Perceived Ease of Use (PEOU) construct consisting of two items (PEOU1 0.582, PEOU2 0.686) is less than 0.7 so the researcher needs to look at it and decide to keep it because of the importance of the item in the construct. In addition, PEOU13 which has 0.893, overall, this indicates that these items have an acceptable relationship for the PEOU construct. In the Perceived Usefulness (PU) construct, three items (PU1, PU2, and PU3) have relatively high factor loadings, which range from 0.646 to 0.828, indicating a strong association with the PU construct. Researchers also have considerations so that they retain item PU3 which has a loading factor of less than 0.7.

In summary, all loading factors of the construct items were above the recommended threshold indicating good measurement reliability and validity. Although slight concerns were raised about the reliability and validity of some of the items, through consideration of the importance of the items and supported by another statistical test results the researcher retained them. Further investigation may be needed to determine the contribution of these items to their respective constructs. The findings of these loading factors are shown in Table 4. The bold values indicate that the factor values for each item are higher than those in other constructs. These values strengthen the discriminant validity.

The constructs AT and BI, AT and PEOU, AT and PU, BI and PEOU, BI and PU, and PEOU and PU showed good discriminant validity results, as Their heterotrait correlations were lower than The threshold of 0.85–0.90 (see Table 5) (Hair et al., 2022). However, The discriminant validity between BI and PEOU and BI and PU is questionable,

Table 4 Cross loadings results

Cross loadings				
	Attitude Toward AI	**Behavioral Intention**	**Perceived Ease of Use**	**Perceived Usefulness**
AT1	**0.774**	0.485	0.542	0.543
AT2	**0.860**	0.611	0.463	0.583
AT3	**0.838**	0.563	0.467	0.604
AT4	**0.749**	0.363	0.577	0.588
BI1	0.585	**0.874**	0.461	0.531
BI2	0.593	**0.908**	0.433	0.610
BI3	0.429	**0.788**	0.296	0.392
PEOU1	0.678	0.548	**0.893**	0.715
PEOU2	0.211	0.047	**0.582**	0.204
PEOU3	0.263	0.174	**0.686**	0.301
PU1	0.691	0.511	0.575	**0.801**
PU2	0.563	0.537	0.586	**0.828**
PU3	0.480	0.433	0.480	**0.768**
PU4	0.416	0.343	0.361	**0.646**

Table 5 Heterotrait-monotrait ratio

Heterotrait-monotrait ratio (HTMT) - Matrix				
	Attitude Toward AI	**Behavioural Intention**	**Perceived Ease of Use**	**Perceived Usefulness**
Attitude Toward AI				
Behavioural Intention	0.753			
Perceived Ease of Use	0.683	0.440		
Perceived Usefulness	0.893	0.741	0.730	

as The hetero-trait correlation between AT and PU (0.893) which is higher than The threshold of 0.85 and close to 0.90 indicates a potential problem with The discriminant validity between The pair of constructs, i.e. The correlation between The AT and PU constructs formed from Their respective items is indicated to be similar, although not so closely related and still within reasonable limits

In Table 5, the HTMT value exceeds the threshold of 0.85. This suggests there may be potential overlap or similarity between the constructs. It is possible that further investigation is needed to determine whether discriminant validity has been adequately established, or it could be that refinement of the items of the constructs is needed to establish adequate discriminant validity between these constructs. In this study, although the HTMT values between some of the constructs were close to the threshold, the researchers still used this model because the Fornell-Larcker and Cross Loading tests showed adequate results. Therefore, discriminant validity can still be considered adequate, although the interpretation of the results needs to be done carefully as recommended by Henseler et al. [44].

The R-Square value indicates the proportion of variance explained by each predictor variable (AT, BI and PU) in the dependent variable or outcome variable. The R-square value for AT was 0.556, BI was 0.448, and PU was 0.447. These values indicate that the model can explain most of the variance in the outcome variable and shows a good fit. The tables show that AT explains 55.6%, BI explains 44.8%, and PU explains 44.7% of the variance in the outcome variable. These R-square values are considered moderate values and indicate that there is a moderate impact of variance on the outcome variable and accounts for a large proportion of the variance. In addition, the moderate R-square values may also indicate a meaningful impact of the predictor variables on the outcome variable, but further analysis and interpretation is required to fully understand the findings and their implications.

3.3 Structural model assessment

The structural model was analysed using the Partial Least Squares Structural Equation Modelling (PLS-SEM) approach and the significance of each path was tested using the bootstrapping technique with 5000 sub-samples. Table 6 presents the results of hypothesis testing, including path coefficients, T-values, and P-values. The hypothesis testing data in Table 6 includes 5 hypotheses (H1: Attitude towards AI influences intention to use; H2: Ease of use of AI influences attitude; H3: Ease of use influences perceived usefulness; H4: perceived usefulness influences attitude; H5: perceived usefulness influences intention to use).

Table 6 Hypothesis test results

	Path Coefficient (C)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	*P* values
AT → BI	0.407	0.411	0.082	4.975	0.000
PEOU → AT	0.272	0.270	0.058	4.708	0.000
PEOU → PU	0.668	0.672	0.036	18.662	0.000
PU → AT	0.536	0.539	0.057	9.475	0.000
PU → BI	0.315	0.311	0.080	3.918	0.000

With the path coefficient and the respective P-value, as commonly used in PLS-SEM in testing the significance of the relationship between variables, it can be seen that all the hypotheses are proven valid. The P-value determines whether the observed relationship between the variables is statistically significant. The path coefficient also represents the strength and direction of the relationship between the predictor variable and the outcome variable. From the results seen in Table 6, it can be seen that: (a) The more positive the attitude towards AI, the higher the behavioural intention to use it; (b) The easier the AI technology is to use, the more positive the attitude towards AI; (c) The easier the technology is to use, the higher the perceived usefulness; (d) The more useful AI is perceived, the more positive the attitude towards AI, and (e) The more useful AI is perceived, the higher the behavioural intention to use it.

The strongest path was found between Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) with Path Coefficient = 0.668 (t = 18.662). This indicates that the easier the AI is to use, the more likely students will find it useful in learning Islam. This finding is in line with the classic TAM theoretical framework which states that perceived ease of use strongly influences perceived usefulness. Perceived Usefulness (PU) also had a significant effect on Attitude Toward AI (AT) with Path Coefficient = 0.536 and (t = 9.475). In other words, students who see tangible benefits from using AI in the context of learning Islam tend to develop a positive attitude towards its use in learning Islam.

Attitude Toward AI (AT) also significantly influences Behavioural Intention (BI) with Path Coefficient = 0.407 and (t = 4.975) indicating that positive attitude plays an important role in shaping the desire to use AI. In addition, Perceived Usefulness (PU) also has a direct influence on Behavioural Intention (BI), with a value of (Path Coefficient = 0.315, t = 3.918), which means that the perceived usefulness of AI (PU) not only shapes attitude (AT), but also directly drives students' intention to use it in learning Islam. Lastly, Perceived Ease of Use (PU) has a significant effect on attitude towards AI (Path Coefficient = 0.272, t = 4.708) which indicates the importance of user-friendly responses, features, and design in shaping positive attitudes towards new technologies. The above findings provide insights into the relationships between variables that inform further analysis and interpretation in the context of the specific research or analysis being conducted. The results of the model structure analysis of the above variables can be seen in Fig. 2.

Based on the above discussion, it can be seen that the five hypotheses in this study are supported, so that this study provides valuable insights and directions as follows: student acceptance of AI in Islamic learning is slightly different from several previous studies that show positive attitudes of students towards AI in their learning process [1, 5, 34]. This research shows that students have a neutral attitude with a slight tendency to accept AI, even though their perception of the usefulness of AI in learning is high. One reason

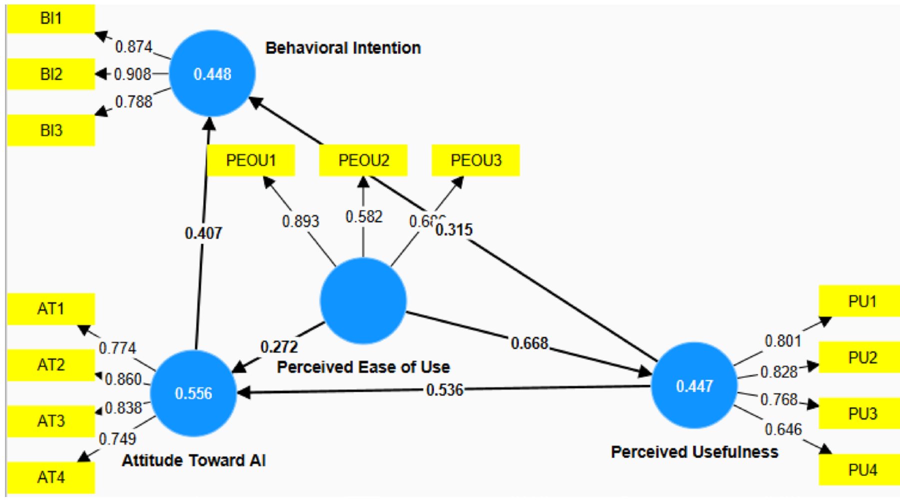

Fig. 2 Path analysis result

that can explain this is the potential negative aspects of AI, such as weak trust in AI information, biased responses, and problems with the accuracy of the AI information itself [16]. This is especially true when it comes to religion and religious beliefs.

The structural model constructed in this research shows that the strongest relationship is between PEOU and PU (path coefficient = 0.668), indicating that perceived ease of use of AI is a key factor in shaping perceived usefulness. Meanwhile, PU also significantly influences AT (0.536) and BI (0.315). This suggests that students who view AI as a useful tool for learning Islam tend to develop positive attitudes and intentions to continue using it. Additionally, students' attitudes (AT), which were also found to be an important predictor of BI (0.407), further strengthen the TAM theory and the theory that attitudes serve as a bridge between perception and actual behaviour [55–57].

4 Conclusion

Muslim students' acceptance of AI in Islamic religious education, based on the results of the analysis described in the previous section, can be summarised as follows: (1) Muslim students' views on the use of AI in learning Islam are neutral, although there is a slight tendency to accept AI. This view influences their intention to use AI in Islamic religious education. In other words, the more positive their views on AI in Islamic religious education, the higher their desire and intention to use it; (2) The ease with which students can use AI is the most decisive or influential factor in their views or attitudes towards AI in using AI and also towards their perception of the usefulness of AI in Islamic religious education. This conclusion suggests that students do not really care about concerns regarding bias, misinformation, and other negative aspects of AI; (3) The usefulness of AI as perceived by students when using AI to study Islam also influences their views or attitudes towards AI. The more useful it is, the better they perceive AI to be. Additionally, the perceived usefulness also influences their intention to use AI in Islamic religious education.

The findings of this study emphasise to educators, especially Islamic education lecturers, the importance of developing AI systems that are in line with Islamic values and ethics in order to improve attitudes and acceptance among Muslim students and demonstrate the importance of responding to and addressing concerns arising from AI, such as ethical challenges, trust, and doubts about the validity of AI content, especially in the context of religious doctrine, which need to be responded to with a critical and reflective approach. The results of this research provide guidance for developers of Islamic educational technology media so that they place greater emphasis on the usefulness and ease of Islamic learning technology in the form of strengthening religious values and ethics that must be maintained when utilising artificial intelligence (AI) in Islamic learning.

The correlation between Perceived Usefulness (PU) and Attitude Towards AI (AT) reinforces the assumption that the perceived practical usefulness of AI greatly influences Muslim students' attitudes towards Islamic learning. This model explains 44.8% of the variance in the intention to use AI (BI), 55.6% in the attitude towards AI (AT), and 44.7% in perceived usefulness (PU). These values are moderate and indicate that the TAM theoretical framework is effective in explaining the dynamics of AI acceptance among Muslim students in the context of religious education. These findings have important implications for the development of technology-based education policies and can be a key focus in AI implementation strategies in higher education, particularly in the field of Islamic religious education at public universities in Indonesia.

This research has limitations in that most of the respondents were students from public universities, even though the number of students from private universities is also large. Almost all of the respondents in this study had a general higher education background, rather than an Islamic higher education background or an Islamic higher education background under the auspices of Islamic boarding schools. In addition, the research data used in this study was non-longitudinal data, so the findings may change in the future due to factors such as the development of more user-friendly AI, policies on the use of AI in universities, or innovations in Islamic religious education. The research could also be biased because the respondents exaggerated or underestimated their responses, which affected the final results of the analysis. There are also limitations to SEM PLS as a statistical analysis technique.

Future research can complement quantitative findings with qualitative research in which data is collected through in-depth interviews or focus group discussions to better understand Muslim students' attitudes towards AI, their perceptions of its usefulness, benefits and experiences of using it. This will certainly provide rich insights and contextual insights that may not be captured by quantitative measurements alone. The next research can also be designed more broadly so that the research sample also includes a balanced number of respondents and informants, not only in Indonesia, but also in other parts of the world.

Guidelines followed statement

The study was performed in accordance with the ethical guidelines of the Institutional Review Board (IRB) at Universitas Negeri Malang https://kep.um.ac.id/.

Author contributions

AUTHORSHIP CONTRIBUTION STATEMENTAs the first and corresponding author, I explain that the article entitled 'Artificial Intelligence (AI) for Muslim students of Higher Education in Islamic Religion Education' is our collaborative paper. We declare that we have individually contributed to the manuscript revising the article entitled 'Artificial Intelligence (AI) for Muslim students of Higher Education in Islamic Religion Education' submitted to Discover Education, as follows: Nur Faizin - Leader in the research and owner of the initial idea in the research conducted that resulted in this article. Muhammad Alfan - Contributed in preparing the abstract and adding limitations to the results of this study.Abdul Basid - Added explanations of the theories used in the article and assisted in conducting the literature review.Mochammad Rizal Ramadhan - Assisted with statistical analysis and interpretation.Siti Aisyah binti Panatik - Assisted in drawing conclusions in this research.Akhmad Nurul Kawakip - Assisted in revising the article in the second stage.We confirm that the contribution of each author has been accurately described above to fairly recognise the role of each contributor in the manuscript.

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Data availability
The data that support the findings of this study have been deposited in the Open Science Framework (OSF) and are available at: https://osf.io/728a4/.

Declarations

Ethics approval and consent to participate
The article is a part of research involving several undergraduate student's participations. All participants provided their informed consent prior to participation, and data collection was conducted with full transparency regarding the purpose and use of the data in this research. In Indonesia, their age is adulthood, therefore neither their parents nor a legal guardian's permission is required.

Consent for publication
The research has been reviewed and approved by the Institutional Review Board (IRB) of Malang State University (UM). Ethical approval was granted with approval number No. Reff: 5.6.4/UN32.14/PB/2025, in accordance with institutional guidelines and international standards for research involving human participants.

Competing interests
The authors declare no competing interests.

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