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Research Article

The Influence of Religiosity Level on AI Acceptance among Islamic Education Students in Blended Learning

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Abstract
The rapid development of artificial intelligence (AI) in higher education has intensified debate about how personal values, including religiosity, shape students' technology acceptance. This study examined the influence of religiosity on AI acceptance and use among students in an Islamic Religious Education program within blended learning. A quantitative correlational design involved 52 students from two classes in Eastern Indonesia. Religiosity was measured using the Centrality of Religiosity Scale (CRS-15), while AI acceptance and use were assessed through a Technology Acceptance Model (TAM)-based instrument. Data were analyzed using simple linear regression after classical assumptions were satisfied. Results showed that religiosity had a significant negative effect on AI acceptance and use ($\beta = -0.45$, $p < 0.001$), explaining 20% of the variance ($R^2 = 0.20$). Students with higher religiosity tended to report lower AI acceptance. These findings highlight the importance of value-sensitive AI integration strategies that respect students' religious perspectives while supporting responsible technology adoption in higher education contexts and pedagogical innovation.

Keywords: AI Acceptance, Blended Learning, Religion, Technology Acceptance Model

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INTRODUCTION

The development of artificial intelligence (AI) in the past decade has transformed the global higher education landscape at an unprecedented pace. A Digital Education Council survey of 3,839 students in 16 countries found that 86% of students use AI in their academic activities, with 54% using AI at least once a week and 24% using it daily (Bollaert, 2025). A similar upward trend was also reported by Freeman in the Higher Education Policy Institute's annual survey with Kortext of 1,041 full-time undergraduate students in the UK, which recorded a gain in the proportion of AI users from 66% in 2023 to 92% in 2024, while the use of generative AI specifically for assignments and exams increased from 53% to 88% over the same period (Döring et al., 2024).

This rapid growth is not only occurring at the individual student level, but is also encouraging universities in various countries to begin integrating AI into academic policies and infrastructure more strategically (Kaya-Kasikci et al., 2025). This phenomenon confirms that the integration of AI in learning is no longer merely a future discourse, but rather an ongoing reality that requires in-depth study from various perspectives, including the values held by its users.

The phenomenon of AI adoption in higher education appears much more prominent when examined in the specific Indonesian context. The 2025 Global Student Survey conducted by Chegg in collaboration with Yonder Consulting on 11,706 students aged 18-21 years in 15 countries found that Indonesia ranked highest in the world in terms of the proportion of students using generative AI to support lectures, reaching 95%, exceeding the global average of 80% (Hidayah et al., 2026). This high usage rate is in line with the findings of a national survey by Tirto and Jakpat in May 2024 of 1,501 school and student respondents aged 15-21 years, which noted that 86.21% of them used AI assistance at least once a month to complete academic assignments (Nurfauziah et al., 2025).

The high rate of AI adoption among Indonesian students is interesting to study further, given that Indonesia is also recorded as having the largest Muslim population in the world, with a proportion reaching 86.9% of the total population (Darmono et al., 2025; Rahiem, 2026; Sari et al., 2025). This condition raises fundamental questions about how the religious values held by the majority of Indonesian students interact with their acceptance of fully automated artificial intelligence technology and the potential to displace the role of human interaction in the learning process.

Although the adoption rate of AI among Indonesian university students is considered very high, research linking AI acceptance with individual religiosity is relatively limited and has yielded inconsistent results. Kozak and Fel, found that students with high levels of religiosity exhibited more intense emotional responses, such as fear and anger, toward AI compared to students with low levels of religiosity, indicating concerns about AI's potential to undermine human values and dignity (Deniz & Stiefenhofer, 2026). However, this finding is not entirely consistent with the results of Turós, study, which used structural equation modeling on 680 respondents, which found that religiosity had no significant direct effect on AI adoption, with the indirect effect only explaining a small portion of the variance (1.9-5.7%) in attitudes toward AI (Rohrbach et al., 2026).

Inconsistent results across studies indicate that the relationship between religiosity and AI acceptance remains complex and highly dependent on the population context and technology use domain studied. On the other hand, research conducted on Indonesian university students by Faizin, using the Technology Acceptance Model (TAM) framework has indeed confirmed that perceived ease of use and usefulness influence attitudes and intentions to use AI among students (Erwin et al., 2026), but this research was specifically limited to the context of religious studies courses, not to the general acceptance of AI in blended learning models that encompass a variety of subjects (Boughanzai et al., 2026). This gap indicates that there has been no empirical study specifically examining the influence of students' levels of religiosity on the acceptance and use of AI in blended learning contexts in general. Therefore, this research is important to fill this gap and provide a more contextual understanding of the interaction between religiosity and the adoption of artificial intelligence technology in Indonesian higher education.

This study used a quantitative correlational approach to examine the influence of religiosity on students' acceptance and use of AI in a blended learning context. Religiosity was measured using the Centrality of Religiosity Scale (CRS-15) developed by Huber and Huber (2012) and validated on Indonesian students (Boughanzai et al., 2026). AI acceptance was measured using Davis's Technology Acceptance Model (TAM) (1989), which focuses on the constructs of perceived usefulness, perceived ease of use, and behavioral intention to use. This second instrument was chosen because it has a proven psychometric basis, allowing the study to focus on examining the relationships between variables without the need to create a new instrument. Data were collected through a survey of students using AI in blended learning and then statistically analyzed to determine the effect of religiosity on AI acceptance, while controlling for relevant demographic variables.

Based on the background explanation above, this study aims to determine the level of religiosity of students in the context of blended learning, determine the level of acceptance and use of AI in students in the same context, and analyze the influence of the level of religiosity on the acceptance and use of AI in students in the blended learning. More specifically, this study is expected to reveal the extent to which religious dimensions play a role in shaping students' attitudes and intentions to accept and utilize artificial intelligence technology as part of the learning process, so that the results of this study can provide a more contextual understanding of the interaction between religious values and the application of technology in the Indonesian higher education environment.

RESEARCH METHOD

Research Design

This research uses a quantitative approach with a correlational design (correlational research). A correlation design was chosen because this research aims to determine whether there is a relationship and the magnitude of the influence between the independent variable, namely religious level, on the dependent variable, namely acceptance and use of AI, without providing treatment or manipulation of the research subjects (Reardon et al., 2018). The research was conducted on students who were or had attended lectures using a blended learning model, which was used as the research context/setting, not as a variable to be tested statistically. Data was collected through a survey with a cross-sectional approach, namely data collection was carried out at a certain point in time on the research sample, so that this research was to describe the condition of the relationship between variables at the time the research took place, rather than observing changes over time. The variables in this study consist of one independent variable (Level of Religiosity) and one attachment variable (acceptance and use of AI), with several demographic variables (such as study program and semester) controlled through sampling criteria. The relationship between variables was analyzed using regression analysis techniques to determine the magnitude of the influence of the level of religiosity on the acceptance and use of AI among students in the blended learning context.

Research Target/Subject

The subjects in this study were students of the Islamic Religious Education Study Program located in Eastern Indonesia, with the research population covering two classes currently studying in the even semester, namely Class A with 25 students and Class B with 27 students, so that the total research population was 52 students. Based on gender, the research population consisted of 20 female students and 32 male students, with an age range of 20 to 24 years. Given the relatively limited population, this study used a saturated sampling technique (total sampling), namely all members of the population were used as research subjects, so that random sampling was not carried out. The characteristics of the research subjects are briefly presented in the following table.

Table 1. Characteristics of Research Subjects

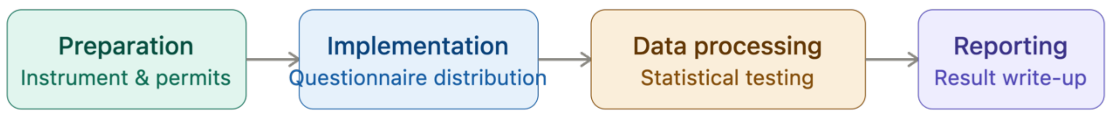
Characteristic	Category	Frequency	Percentage
Class	Class A	25	48.1%
	Class B	27	51.9%
Gender	Female	20	38.5%
	Male	32	61.5%
Age	20-24 years	52	100%
Total		**52**	**100%**

Research Procedure

This research was conducted through several systematic stages, starting from the preparation stage, implementation, to data processing and analysis, as described below. The preparation stage began with the preparation of a research proposal, literature review, and the development of a conceptual framework and research hypothesis. Next, the researcher developed a research instrument based on an adaptation of The Centrality of Religiosity Scale (CRS-15) and the Technology Acceptance Model (TAM), which was then consulted with the supervisor for approval. The approved instrument was then issued to obtain research permits from the study program and the institution where the research was conducted.

The implementation phase began with the bold distribution of questionnaires to all research subjects, namely Class A and Class B students of the Islamic Religious Education Study Program. Before completing the questionnaire, research subjects were first given an explanation of the research objectives, guaranteed data confidentiality, and asked to provide informed consent to participate voluntarily. Data collection was carried out over a certain period of time until all research subjects had completed the questionnaire. The collected data were then checked for completeness (data cleaning), scored according to the scoring guidelines for each instrument, and then input into a statistical data processing program. Next, instrument validity and reliability tests were conducted, classical assumption tests (normality, linearity, and homoscedasticity), and hypothesis testing using regression analysis to determine the effect of religiosity levels on the acceptance and use of AI.

The final stage of this research is the preparation of a research report, which includes the interpretation of the results of data analysis, a description of the findings linked to the literature review, drawing conclusions, and compiling recommendations for further research.



Future 1. Research Procedure

Instruments, and Data Collection Techniques

This study used two main instruments to measure the independent and dependent variables: a scale of religiousness and a scale of acceptance/use of AI. The second instrument was constructed as a closed-ended questionnaire with a Likert scale, which was freely distributed to all research subjects. Students' religiosity was measured using the Centrality of Religiosity Scale (CRS-15) developed (Huber & Huber, 2012) and adapted into Indonesian and tested for construct validity on a sample of Muslim students through Confirmatory Factor Analysis (CFA) by Chairani et al. (2023). This instrument consists of 15 items that measure five dimensions of religiosity: intellectual, ideological, public ritualistic, individual ritualistic, and experiential/deepening, with each dimension represented by three items. Each item was answered using a Likert scale of 1-5, ranging from "never/very low" to "very often/very high." The instrument's religiosity scale is presented in Table 2.

Table 2. Religiosity Level Instrument Grid

Dimension	Indicator	Number of Items	Item Numbers
Intellectual	Frequency and interest in thinking about religious issues	3	1, 2, 3
Ideology	Strength of belief in the existence of God and transcendent reality	3	4, 5, 6
Public Religious Practice	Involvement in religious activities within the community	3	7, 8, 9
Private Religious Practice	Personal worship and prayer practices	3	10, 11, 12
Experience/Religious Feeling	Subjective experience of feeling God's presence	3	13, 14, 15

AI acceptance and use were measured using an instrument developed based on Davis's (1989) Technology Acceptance Model (TAM) framework, which encompasses four main constructs: Perceived Effectiveness (PU), Perceived Ease of Use (PEOU), Attitude Toward Use (ATU), and Behavioral Intention to Use (BI). Each statement was answered using a 1-5 Likert scale, ranging from "strongly disagree" to "strongly agree." The AI acceptance and use instrument grid is presented in Table 3.

Table 3. AI Acceptance and Use Instrument (TAM) Grid

Construct	Indicator	Number of Items
Perceived Usefulness (PU)	Perceived benefit of AI for the learning process	4
Perceived Ease of Use (PEOU)	Perceived ease of using AI	4
Attitude Toward Using (ATU)	Attitude toward the use of AI in learning	4
Behavioral Intention to Use (BI)	Intention to continue using AI in learning	3

Before being used for data collection, both instruments were tested for validity and reliability on the research subjects. Validity testing was conducted using product-moment correlation to determine the discriminatory power of each item, while reliability testing was conducted using Cronbach's Alpha coefficient to determine the internal consistency of the instrument. An alpha value of ≥ 0.70 is considered to meet the criteria for adequate reliability (Taber, 2018).

Data Analysis Technique

The collected data was analyzed through three main stages: instrument testing, classical assumption testing, and hypothesis testing, with each technique used based on methodological considerations appropriate to the characteristics of the research data.

Before the data were used to test the hypotheses, validity and reliability tests were conducted on both research instruments. Validity testing was performed by calculating the product-moment correlation between each item's score and the total score. An item was declared valid if the correlation value (r calculated) was greater than r table at a significance level of 5%. Reliability testing was conducted using Cronbach's Alpha coefficient, with the instrument considered reliable if the alpha value reached or exceeded 0.70, referring to the criteria proposed by (Taber, 2018) regarding internal consistency standards for psychological instruments.

Furthermore, before conducting the hypothesis testing, the data were pre-tested to ensure that the assumptions of classical regression were met. Normality testing was conducted using the Shapiro-Wilk test, not the Kolmogorov-Smirnov test, considering the relatively small population size of this study (n = 52). Meanwhile, Razali and Wah (2011) through Monte Carlo simulations proved that the Shapiro-Wilk test has greater statistical power in the high range of normality than the Kolmogorov-Smirnov, Lilliefors, and Anderson-Darling tests, especially in small sample sizes. Linearity testing was conducted to determine whether there is a linear relationship between the religiosity level variable and the acceptance variable and there is the use of AI, considering that the linearity assumption is a fundamental prerequisite for the validity of the linear regression model (Nerenberg et al., 2018a).

Homoscedasticity testing was conducted using the Glejser test to ensure that the residual variance is constant and does not form a certain pattern, because violation of this assumption can cause the regression coefficient estimates to be inefficient but remain unbiased (Jiménez-Gamero et al., 2025). Hypothesis testing was conducted using simple linear regression analysis, considering that this study involved one independent variable (level of religiosity) and one engagement variable (acceptance and use of AI), each of which was processed as a composite score of the total instrument items, so that the multiple regression model and structural modeling measured were not appropriate for the limited size of the study population (Hair & Alamer, 2022).

The regression model used was formulated as Y = a + bX + e, where Y is the acceptance and use of AI, X is the level of religiosity, a is a constant, b is the regression coefficient, and e is the error term. The significance of the effect was tested using a t-test at a significance level of 5% (α = 0.05), with the H_0 testing criteria being rejected if the significance value is less than 0.05, which means there is a significant effect of the level of religiosity on the acceptance and use of AI. The magnitude of the contribution of the independent variable to the engagement variable is then known through the coefficient of determination (R^2) value.

RESULTS AND DISCUSSION

Prior to hypothesis testing, the reliability of both instruments was assessed using Cronbach's alpha. The religiosity scale demonstrated excellent internal consistency (α = .91), and the AI acceptance scale demonstrated good internal consistency (α = .85), both exceeding the commonly accepted threshold of .70 (Sighencea et al., 2022). Normality of the two continuous variables was examined using the Shapiro-Wilk test, selected over the Kolmogorov-Smirnov test given the small sample size (Yazici & Yolacan, 2007). Results indicated that both religiosity (W = .98, p = .668) and AI acceptance (W = .98, p = .616) did not significantly deviate from normality. Skewness (religiosity = 0.12; AI acceptance = - 0.24) and kurtosis (religiosity = - 0.39; AI acceptance = 0.04) values fell within the acceptable range of ±1, further supporting the normality assumption (Nerenberg et al., 2018b). Homoscedasticity was examined using the Glejser test, which was non-significant (b = 0.06, p = .394), indicating no evidence of heteroscedasticity in the residuals.

Table 4. *Descriptive Statistics for Study Variables (N = 52)*

Variable	M	SD	Min	Max	Skewness	Kurtosis
Religiosity (CRS-15)	3.49	0.46	2.62	4.53	0.12	- 0.39
AI Acceptance (TAM)	3.61	0.39	2.54	4.39	- 0.24	0.04

A simple linear regression was conducted to examine whether religiosity predicted AI acceptance among students in a blended-learning context. The overall model was statistically significant, $F(1, 50) = 12.65$, $p < .001$, and explained a moderate proportion of variance in AI acceptance, $R^2 = .20$, corresponding to a medium-to-large effect size (Cohen's $f^2 = .25$; Cohen, 1988). Religiosity was a significant negative predictor of AI acceptance, $b = -0.38$, 95% CI [-0.60, - 0.17], $\beta = -.45$, $t(50) = -3.56$, $p < .001$. These results indicate that for every one-unit increase in religiosity, AI acceptance decreased by approximately 0.38 units, holding other factors constant.

Table 5. *Summary of Simple Linear Regression Predicting AI Acceptance from Religiosity*

Predictor	*b*	*SE*	95% CI	*β*	*t*	*p*
Constant	4.95	0.39	[4.16, 5.73]	—	12.62	< .001
Religiosity	- 0.38	0.11	[- 0.60, - 0.17]	- .45	- 3.56	< .001

Note. $R^2 = .20$, adjusted $R^2 = .19$, $F(1, 50) = 12.65$, $p < .001$.

The present study examined the relationship between religiosity and AI acceptance among university students engaged in blended learning. Consistent with the hypothesis, religiosity emerged as a significant negative predictor of AI acceptance, accounting for approximately 20% of the variance a medium-to-large effect by conventional benchmarks (Deshen et al., 2026). This finding is broadly consistent, who reported that university students with higher religiosity exhibited more intense negative emotional responses (fear and anger) toward AI, which the authors interpreted as reflecting concerns about AI's potential threat to human dignity and uniqueness (Kozak & Fel, 2024). The present findings extend this line of work by demonstrating that such affective caution may translate into measurably lower behavioral acceptance, not merely emotional discomfort.

However, the present results diverge from those of Turós et al. (2025), who found that intrinsic religiosity exerted no significant direct effect on AI adoption among Catholic secondary school teachers, with indirect effects explaining only 1.9-5.7% of variance in AI attitudes. Several explanations may account for this discrepancy. First, the populations differ substantially — university students navigating identity exploration (Arnett, 2000) may respond differently to value-technology conflicts than established professionals with formed occupational identities. Second, Turós et al. (2025) operationalized AI adoption narrowly, limited to five discrete usage behaviors, which the authors themselves noted may not have engaged the deeper, identity-relevant dimensions of religiosity. The present study's TAM-based measure, which captures attitudinal and intentional dimensions of acceptance rather than narrow behavioral frequency, may be more sensitive to value-based influences.

Demonstrated that perceived ease of use and perceived usefulness significantly predicted Muslim students' attitudes and behavioral intention toward AI in Islamic religious education contexts. The present study extends this TAM-based evidence by showing that religiosity itself as a distal, value-based construct may shape the very attitudes and perceptions that proximally drive acceptance, suggesting a potentially layered model in which religiosity operates upstream of TAM's cognitive-rational predictors.

These findings suggest that dominant technology acceptance frameworks such as TAM, which emphasize cognitive-rational antecedents (Davis, 1989), may benefit from incorporating value-based and identity-relevant constructs, particularly in populations for whom religious identity is psychologically central. This aligns with recent calls in the literature to extend TAM and UTAUT beyond purely utilitarian predictors (Turós et al., 2025).

For higher education institutions implementing AI-supported blended learning, these findings suggest that a one-size-fits-all approach to AI integration may be insufficient. Institutions may need to address religiously grounded concerns — such as perceived threats to human dignity or authentic learning relationships — through transparent communication about AI's role as a supplementary rather than substitutive tool, rather than relying solely on utility-focused messaging.

Several limitations warrant caution in interpreting these findings. First, the cross-sectional design precludes causal inference; it remains possible that lower AI acceptance leads individuals to seek meaning in religiosity, rather than the reverse. Second, the small sample size (N = 52) limits statistical power and generalizability beyond the studied population, consistent with recommendations that findings from convenience samples of this size be interpreted as population-specific rather than broadly generalizable (Hair et al., 2019). Third, common method bias may have inflated observed associations, as both constructs were measured via self-report at a single time point. Future research should employ longitudinal designs and larger, more diverse samples to establish the temporal and causal ordering of these constructs.

CONCLUSION

This study examined the influence of religiosity on AI acceptance among university students in a blended learning context. Using a quantitative correlational design with a validated 15-item religiosity scale (CRS-15) and a Technology Acceptance Model (TAM)-based instrument, the findings demonstrated that religiosity significantly and negatively predicted AI acceptance, $b = -0.38$, $\beta = -.45$, $p < .001$, accounting for approximately 20% of the variance in students' acceptance of AI-supported learning tools. These results indicate that students with higher levels of religiosity reported comparatively lower acceptance of AI in their learning environment, a pattern consistent with prior evidence linking religiosity to heightened caution toward AI (Kozak & Fel, 2024), though at odds with studies reporting negligible direct effects in other populations (Turós et al., 2025).

This study makes three contributions to the literature. First, it extends technology acceptance research by empirically testing religiosity as a distal predictor within a TAM framework, addressing a gap noted by prior researchers regarding the underrepresentation of value-based constructs in dominant acceptance models (Turós et al., 2025). Second, it contributes context-specific evidence from a population and setting — Muslim university students in a blended learning environment — that has received limited empirical attention relative to studies conducted in other cultural and religious contexts. Third, it offers preliminary support for the proposition that religiosity may influence AI acceptance not only through affective channels, as previously demonstrated (Kozak & Fel, 2024), but also through measurable behavioral intention and attitudinal outcomes captured by established technology acceptance constructs.

From a practical standpoint, the findings suggest that higher education institutions integrating AI into blended learning curricula should not assume uniform receptivity to these tools across their student populations. Institutions may benefit from developing communication and onboarding strategies that explicitly address value-based concerns — such as the preservation of authentic teacher-student relationships and human judgment in learning — alongside conventional utility-focused framing, particularly when serving religiously engaged student populations.

Nonetheless, these conclusions should be interpreted in light of several limitations. The cross-sectional design precludes causal claims regarding the direction of the observed relationship, the relatively small and geographically bounded sample ($N = 52$, two classes within a single region) limits generalizability to broader student populations, and reliance on self-report measures introduces the possibility of common method bias. Future research should adopt longitudinal or experimental designs, incorporate larger and more heterogeneous samples across multiple institutions, and examine potential mediating mechanisms — such as perceived threat to human dignity or perceived loss of authentic learning — through which religiosity may shape technology acceptance. Investigating moderating factors, including digital literacy and prior AI exposure, would further clarify the boundary conditions under which this relationship holds.

DECLARATION OF AI AND AI ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

During the preparation of this work, I, as the author, used Claude AI to assist in reviewing articles relevant to the research. After using this tool/service, I reviewed and edited the content as needed and take full responsibility for the published content.

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AUTHOR CONTRIBUTIONS

Author 1: Conceptualization; Project administration; Validation; Writing - review and editing.

Author 2: Conceptualization; Data curation; In-vestigation.

Author 3: Data curation; Investigation.

DECLARATION OF COMPETING INTEREST

The authors declare that they have no known financial, professional, personal, or institutional competing interests that could have influenced the research, interpretation of the findings, or preparation of this manuscript. The authors confirm that the study was conducted independently and that no relationships or circumstances exist that could reasonably be perceived as affecting the objectivity or integrity of the work.

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