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AI Readiness in 21st-Century Islamic Education: Teachers Behavioral Intentions and Perceived Control

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Abstract
This study investigates the determinants of AI adoption among Islamic Religious Education teachers within the 21st-century learning paradigm. Grounded in the TPB, it examines how attitudes, subjective norms, and perceived behavioral control shape teachers' intentions and actual behaviors regarding AI integration. A quantitative survey was conducted via online questionnaires distributed to 150 islamic religious education teachers in Tanjung Jabung Barat Regency, Jambi. Data were analyzed using SmartPLS 3 for PLS-SEM. Results indicate that perceived behavioral control was the most significant predictor, strongly influencing intention with coefficient = 0.586, p <0.001 and behavior with coefficient = 0.300, p = 0.021. Subjective norms also significantly affected intention with coefficient = 0.278, p = 0.001. Conversely, attitudes had no direct impact on intention (p = 0.681) but significantly predicted behavior with coefficient = 0.432, p <0.001. The model demonstrated strong explanatory power. Accounting for 65.8% of intention variance and 78.9% of behavior variance, affirming TPB's efficacy in understanding technology adoption among Islamic religious education teachers. These findings underscore the critical role of teachers' self-efficacy and social influence in AI adoption. Practical interventions, such as hands-on training and fostering supportive environments, are essential for successful integration. Future research could explore mediating variables or qualitative approaches to deepen understanding of barriers and facilitators.

Keywords: Artificial Intelligence; Islamic Religious Education; Theory of Planned Behavior

INTRODUCTION

Recent technological advancements have significantly contributed to improving work efficiency and facilitating the fulfilment of human needs. As noted by Tjahyanti et al. (2022), these technological innovations can also be leveraged within the educational sector. Artificial Intelligence (AI), in particular, has garnered widespread attention and is poised to simplify daily activities, including offering innovative and engaging learning experiences. Chat GPT, a form of AI, offers numerous benefits for students, such as enhancing their participation in learning activities, boosting motivation, and developing their skills (Diantama, 2023). Research by Sucahyo et al. (2023) demonstrates that AI plays a pivotal role in fostering student creativity through AI-driven projects, such as the Strengthening Pancasila Student Profile (P5) initiative, which focuses on innovative learning methods. Furthermore, AI is revolutionizing computer-assisted education, ushering in a new era. Bakti et al. (2023) suggest that educators can utilize AI to enhance assessment practices, streamline data collection, improve learning processes, and devise new teaching strategies. Meanwhile, students benefit from intelligent tutoring systems and asynchronous learning approaches that help maximize their educational outcomes.

AI offers numerous benefits across various sectors of life. In the marketing field, AI helps gather insights by analyzing visitor behavior, tracking website performance, and segmenting audiences (Saefudin et al., 2023). Additionally, AI has been applied in agricultural innovation, such as the development of automated rice irrigation systems, which can assist or even replace the labor-intensive task of irrigating rice fields, making the process more efficient and autonomous (Setiawan & Anggraeni, 2018). According to Rahayu Meliani & Suryadi (2017), AI-driven games can stimulate critical thinking in individuals who play against computers. Sabella et al. (2023) further highlight that participants in AI-based game development training were highly engaged, showcasing the technology's potential to captivate users. Moreover, AI is also being utilized in decision-making processes, such as evaluating job applications, where techniques like Artificial Intelligence Rough Set and Rosetta Software are employed to provide accurate and reliable results (Wijaya, 2018).

Islamic Religious Education plays a crucial role in character development and offers significant opportunities to integrate AI to enhance the quality of the learning process. As we progress further into the 21st century, the rapid development of educational technology presents both opportunities and challenges for Islamic Religious Education. Teachers in this field are now expected not only to possess strong knowledge of religious content but also to be proficient in using technological tools to effectively deliver this material. According to Rahmawati (2022), the 21st-century learning models have shown positive impacts on students' mastery of the subject matter and have contributed to better learning outcomes, including in Islamic Religious Education. Salsabila et al. (2020) emphasize that, in this technological age, educational technology must be integrated into every aspect of teaching and learning, ensuring optimal educational outcomes, particularly in Islamic Religious Education. However, despite the recognition of its importance, teachers face considerable challenges in implementing technology effectively. Putriana et al. (2024) note that although many teachers acknowledge the value of technological tools in enhancing the learning process, their skills and expertise in using digital technologies remain limited, hindering the desired improvements in educational quality. Research by Abdillah & Astutik (2024) reveals that while technology is being incorporated into Islamic Religious Education, full implementation is often restricted due to technological limitations. Musyafak & Subhi (2023) further assert that by incorporating interactive and innovative teaching methods such as e-learning platforms, multimedia, and collaborative projects, educators can engage students more effectively and deepen their understanding of Islamic principles. While the integration of technology in Islamic Religious Education is essential for improving learning outcomes, adequate teacher training, robust technological infrastructure, and supportive policies are crucial to fully realizing its potential. Therefore, understanding the factors that influence educators' adoption of innovations like AI in Islamic education is essential for fostering its successful integration.

As highlighted by Khafifatulfian & Misbah (2023), the 21st-century learning environment can be enhanced through the application of quantum, cooperative, and differentiated learning models, which educators may consider integrating into Islamic Religious Education. Strengthening this approach, the teachings of Imam Nawawi in Al-Arba'in An-Nawawiyah emphasize twelve key principles for Islamic learning in the 21st century, namely: 1) Strategy, 2) Model, 3) Approach, 4) Material, 5) Method, 6) Technique, 7) Media, 8) Evaluation, and 9) Remedial (Rahmat, 2021). Luthfan et al. (2024) further stress the need for appropriate teaching methods in Islamic Religious Education, such as technology-based, collaborative, problem-based, experience-based, inquiry-based, project-based, interactive, and inclusive approaches, all of which are essential for aligning education with the demands of the 21st century. Additionally, Salsabila et al. (2020) assert that the integration of educational technology in Islamic Religious Education is crucial for fostering innovation and creativity within the learning process. This alignment of technology with contemporary teaching methods is vital to meet the evolving needs of students in today's rapidly advancing educational landscape.

One theoretical framework that can be employed to analyze the integration of technology in education is the Theory of Planned Behavior (TPB). According to this theory, a person's intention to engage in a specific behavior is shaped by three key factors: their attitude towards the behavior, subjective norms, and perceived behavioral control (Ajzen, 1991). TPB has been widely applied in educational research to predict the adoption of educational technologies. For instance, Habibi et al. (2023) used TPB to examine how student teachers' beliefs and understanding of technology influence their acceptance and use of technology in teaching. Moreover, the TPB model has been further enriched by incorporating the Technological Pedagogical Content Knowledge (TPACK) framework, which serves as an indicator of a teacher’s ability to effectively integrate technology into the learning process. However, the application of TPB in the context of AI in Islamic Religious Education remains underexplored. This gap in the literature is what this research seeks to address, providing new insights into how AI can be integrated into this educational domain.

Islamic education in the 21st century is undergoing a profound transformation, driven by technological advancements, particularly the rise of Artificial Intelligence (AI), which has the potential to revolutionize learning processes. However, the successful integration of AI into teaching largely depends on the psychological and behavioural readiness of teachers. In this regard, the Theory of Planned Behaviour (TPB) provides an effective framework for analysing the factors influencing teachers' intentions to adopt AI. According to TPB (Ajzen, 1991), an individual's intention to engage in a particular behaviour is shaped by three primary factors: (1) attitude toward the behavior, (2) subjective norms, and (3) perceived behavioural control (PBC). Previous research has shown that these factors significantly influence teachers' intentions and actual behaviours, including in contexts such as inclusive education (Urton et al., 2023) and responses to accessibility challenges (Siqueira et al., 2022). Additionally, She et al. (2024) extended TPB’s application to financial behaviour, identifying PBC as the most significant predictor of behavioral intention. In the context of technology-driven Islamic education, PBC plays a pivotal role, as teachers often encounter technical, cultural, and institutional challenges when implementing digital innovations. Therefore, understanding the psychological and behavioral dynamics that shape teachers' intentions and their perceived behavioral control is crucial for assessing and enhancing AI readiness in contemporary Islamic education. By utilizing the TPB framework, this study aims to provide valuable insights into the psychosocial factors affecting AI adoption, while also offering policy recommendations to support and empower teachers in the digital era.

While the adoption of educational technology has been extensively studied, there remains a significant gap in research regarding the psychological factors influencing Islamic Religious Education (IRE) teachers' acceptance and use of Artificial Intelligence (AI), especially within the context of AI integration in Islamic education through a behavioral theory framework. The TPB has been applied in various studies on educational technology adoption, such as the acceptance of technology by pre-service teachers (Habibi et al., 2023) and entrepreneurial intentions (Soelaiman et al., 2023). However, there is still limited understanding of how the components of TPB attitudes, subjective norms, and perceived behavioral control, specifically affect the intentions and behaviors of IRE teachers in adopting AI. This gap is further highlighted by the fact that most previous research has focused primarily on technical aspects or generic technology implementation, neglecting the unique psychosocial dynamics present in Islamic education settings. This study aims to fill this gap by providing empirical evidence based on the TPB within the context of Islamic Religious Education, offering new insights into the adoption of AI by IRE teachers insights that have not been fully explored in existing literature.

In the field of entrepreneurship, Soelaiman et al. (2023) examined the influence of role models on shaping students' entrepreneurial intentions by applying the TPB. Their study found that positive attitudes towards entrepreneurship, combined with the influence of role models, significantly contribute to the development of entrepreneurial intentions. This finding aligns with Harnoko & Herianingrum (2020), who demonstrated that perceived behavioral control plays a crucial role in an individual's decision to take out a home loan, illustrating how individuals manage risks and opportunities in financial decisions. Similarly, Saputra (2019) conducted a study on tax compliance using the TPB framework, revealing that individuals' attitudes towards tax obligations, along with social norms that encourage compliance, significantly influence tax-paying behavior. This conclusion is further supported by Yulianti & Salsabilla (2022), whose research on adolescent compliance with blood supplement intake shows that both attitudes and social norms are key factors in shaping health behaviors among young individuals. Islamic religious education teachers in 21st century learning cannot only rely on lecture methods but must also utilize educational technology such as multimedia, gamification and digital platforms to attract students in the current generation, namely generation Z and Generation Alpha, but the use of educational technology also requires mental and technical readiness of teachers which can be influenced by personal beliefs, social environment and availability of facilities, factors which are at the heart of the discussion in TPB.

This study aims to thoroughly explore the factors that influence the intentions and behaviors of Islamic Religious Education (IRE) teachers in adopting AI for their teaching activities. Specifically, the research will examine how attitudes, subjective norms, and perceived behavioral control shape the behavioral intentions of IRE teachers to integrate AI into their practices. Additionally, the study will assess the direct impact of attitudes and PBC on the actual use of AI by teachers, while also investigating how behavioral intentions serve as a predictor of AI adoption in the classroom. Beyond enhancing our understanding of AI usage in Islamic Religious Education, this research also contributes to expanding the application of the TPB within this educational context. The findings are expected to provide valuable insights for technology developers, policymakers, and educational institutions, guiding the design of training programs and the development of infrastructure that supports the integration of AI into teaching and learning. This will enable Islamic Religious Education to remain dynamic and relevant, aligning with the latest technological advancements and contributing to the improvement of educational quality in the digital era.

RESEARCH METHODS

This study employs a quantitative research approach, which is particularly suited for examining the relationships between variables through numerical data. The research adopts a survey method, allowing for the gathering of data from natural settings (Hirose & Creswell, 2023). This approach involves distributing questionnaires and other tools to capture participants' responses, providing valuable insights into the variables under study. By utilizing this method, the study aims to explore how various psychological factors influence IRE teachers' adoption of AI in their teaching practices.

Central to this research is the application of the TPB, which serves as the theoretical framework for understanding the behavioral intentions of IRE teachers towards AI adoption. TPB suggests that attitudes, subjective norms, and perceived behavioral control significantly shape individuals' intentions to engage in specific behaviors (Bosnjak et al., 2020). In this study, these variables are tested to determine how they influence teachers' intentions and actual behaviors in incorporating AI into their teaching methods. By exploring the interactions between these factors, the study aims to provide a comprehensive understanding of the psychological and behavioral dynamics behind AI adoption in the context of Islamic education. According to (Rahmanita et al., 2021) intention in research is a mediating variable, a mediating variable is a variable that influences the relationship between the independent variable and the dependent variable into an indirect relationship.

The research further investigates the direct influence of factors attitude, subjective norms, and perceived behavioral control on teachers' actual use of AI. For instance, it explores how teachers' positive attitudes toward AI impact their intention to use it, and how perceived behavioral control affects their confidence in integrating AI into their teaching. Additionally, the study examines how these factors, combined with behavioral intentions, ultimately affect teachers' behaviors in accessing and using AI in the learning process. This approach offers a detailed analysis of the factors that directly and indirectly influence the adoption of AI, shedding light on key motivators and barriers to its integration. The investigation in this study focused on five hypothesis formulations which include:

H1 : The teacher's attitude of desire to learn has a positive effect on the teacher's mandatory intention to access behavior AI.
H2 : Subjective norms have a positive effect on teachers' intentions to behave accessible AI.
H3 : Perceived behavioral control has a positive effect on teachers' mandatory intention to behave in order to access AI.
H4 : The teacher's attitude has a direct positive effect on teacher behavior in accessing AI.
H5 : Perceived behavioral control has a direct positive effect on teacher behavior in accessing AI.
H6 : Intention to behave obediently has a positive effect on teacher behavior in accessing AI.

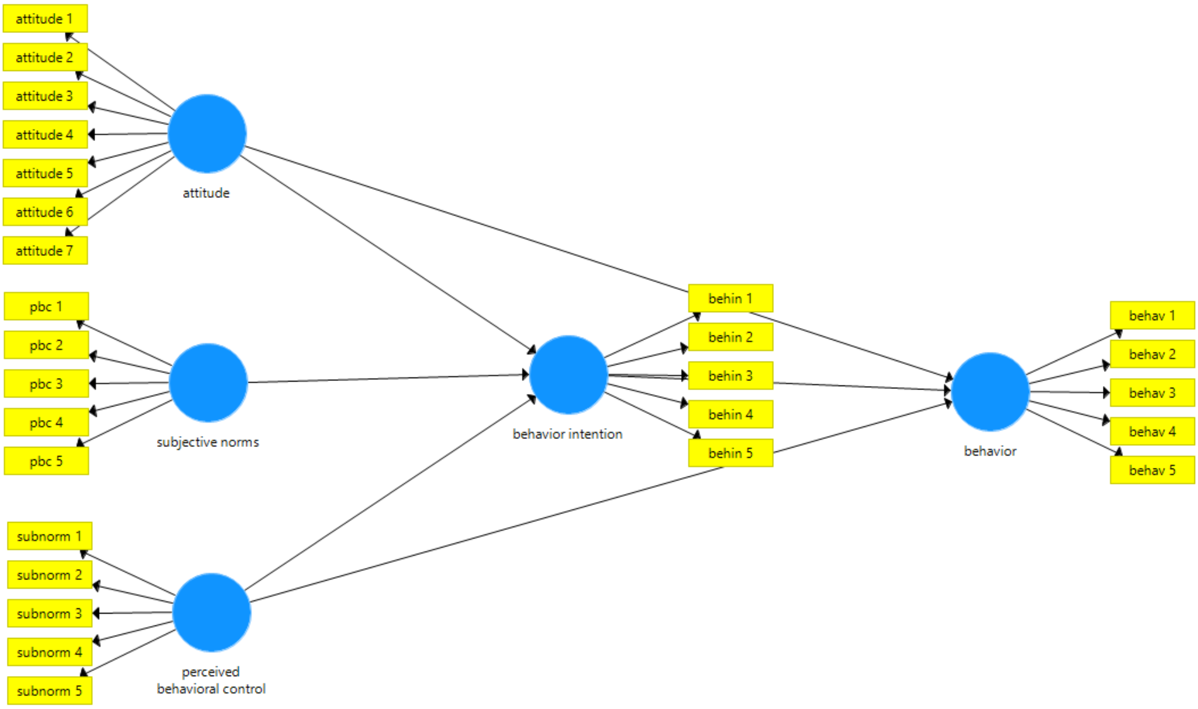

Figure 1. Variable Hypothesis Theory of Planned Behavior

Research Design

The instrumentation process is adapting and constructing items in the survey which are centered on the five main domains of the theory of planned behavior, specifically attitudes, objective norms, perceived behavioral control, behavioral intention to use, and behavior. This instrument is adapted from previous research on the TPB (Ajzen, 2011). Then the scale created was a 5-point Likert scale with anchors starting from 1 with the statement strongly disagree to 5 with the statement strongly agree. This instrument is translated from English to Indonesian and vice versa. For this purpose, two experts were involved. The questionnaires were compared to see whether the translation in the context of practicing teachers through face and content validity processes was appropriate for clarity and simplicity of expression (Connell et al., 2018). The instrument was then distributed to three experts to calculate the content validity index (CVI). Each item is presented for evaluation of relevance, simplicity, and clarity. Items are on a 5-point scale, ranging from 1 (not relevant or not simple or not clear) to 5 (very relevant or very simple or very clear) (Lynn M. R., 1986). To carry out further evaluations, scilicet validity and reliability, the remaining indicators were distributed for a pilot study to 150 teachers of Islamic religious education subjects. Using SmartPLS 3, data were calculated for Cronbach's alpha evaluation, which aims to report preliminary reliability before main data collection. No construct has an alpha value below the threshold of 0.700 (Hair & Alamer, 2022). Varimax rotation was performed to disentangle the factors involved in the instrument through an exploratory factor analysis procedure. In this instrumentation procedure, several exploratory measurements are carried out; Bartlett's Test of Sphericity that should exist P <0.005, the factor loading should be a value of 0.500, Kaiser-Meyer-Olkin with a value of >0.800, and Community of 0.300. The description of the data collection instruments is presented in Table 1.

Table 1. Data collection instrument

Variable	Dimensions/Indicators	Number of Items	Scale Type	Source/Adaptation
Attitude	Beliefs about the outcomes of using AI in teaching (e.g., "Using AI makes my teaching more effective," "Using AI makes learning more engaging for students"). Evaluation of these outcomes (e.g., "Effective teaching is good," "Engaging learning is desirable").	7	5-point Likert	Adapted from (Ajzen, 2011) and similar TPB studies.
Subjective Norms	Perceived social pressure to use AI (e.g., "My colleagues expect me to use AI in teaching," "School administration encourages AI use"). Motivation to comply with these expectations.	5	5-point Likert	Adapted from (Ajzen, 2011) and similar TPB studies.
Perceived Behavioral Control	Perceived ease or difficulty of using AI (e.g., "I have the necessary resources to use AI," "I have the skills to integrate AI into my lessons"). Self-efficacy in using AI.	5	5-point Likert	Adapted from (Ajzen, 2011) and similar TPB studies.
Behavioral Intention	Likelihood of future AI use (e.g., "I intend to use AI regularly in my teaching next semester," "I plan to explore new AI tools for my lessons").	5	5-point Likert	Adapted from (Ajzen, 2011) and similar TPB studies.
Behavior	Actual frequency and extent of AI use in teaching (e.g., "I frequently use AI for lesson planning," "I have successfully integrated AI into student activities").	5	5-point Likert	Self-developed based on TPB behavior component.

Data Collection

During the data collection process, the survey was distributed via an online survey application, specifically using Google Forms, an application developed by Google Inc. The sample of respondents, determine use a sample size calculator, according to Johnston et al. (2019). The sample size calculator is considered very simple and useful for researchers who do not have a strong mathematical background. A newly developed web-based sample size calculator, which includes the ability to calculate sample size from four important coefficients (Hakim et al., 2018). So, the sample was determined to be more than 150 respondents. The survey was distributed to Islamic religious education teachers in West Tanjung Jabung Regency, Jambi Province and all respondent answer data was stored in Microsoft Excel and transferred to the SmartPLS 3 application. The gender distribution is shown in Figure 2 below.

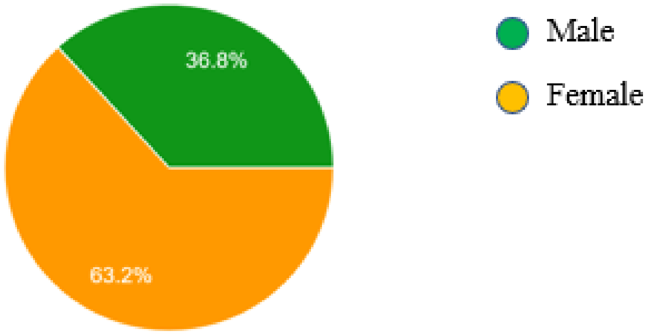

Figure 2. Gender of Respondents

Data Analysis

The collected data were initially stored in Microsoft Excel and then imported into SmartPLS 3 for analysis. The Partial Least Squares Structural Equation Modeling (PLS-SEM) method was chosen because it is suitable for complex models with both reflective and formative constructs, as well as its ability to handle non-normally distributed data and relatively small sample sizes compared to covariance-based SEM (Hair et al., 2017). The data analysis process in SmartPLS 3 consists of two main stages:

1. Measurement Model Evaluation

This stage aims to assess the reliability and validity of the constructs to ensure that the indicators accurately measure the intended concepts. The evaluated criteria include:

1) Indicator Loadings: Reflective indicator loadings should be >0.708
2) Indicators with values below this threshold may be considered for removal (Hair et al., 2019)
3) Internal Reliability: Measured using Cronbach's Alpha (α) and Composite Reliability (CR). Acceptable values are α >0.700 and CR >0.708 (Hair & Alamer, 2022).
4) Convergent Validity: Assessed through Average Variance Extracted (AVE). An AVE value >0.500 indicates that a construct explains more than 50% of the variance of its indicators (Hair & Alamer, 2022).
5) Discriminant Validity: Tested using the Fornell-Larcker criterion and Heterotrait-Monotrait Ratio (HTMT). According to the Fornell-Larcker criterion, the square root of a construct's AVE should be greater than its correlation with other constructs. Meanwhile, the HTMT value should be <0.90 (or <0.85 for stricter testing) to ensure construct distinctiveness (Henseler et al., 2015).
6) Multicollinearity: Measured using the Variance Inflation Factor (VIF). A VIF value <5 indicates no significant multicollinearity issues (Hair et al., 2017).

2. Structural Model Evaluation

This stage aims to examine the relationships between constructs (hypotheses). Key aspects assessed include:

1) Path Coefficients (β): Indicate the strength and direction of relationships between constructs. The significance of coefficients is tested using the bootstrapping method (5,000 subsamples with no sign changes).
2) R^2 Value: Represents the proportion of variance in the endogenous construct explained by exogenous constructs. A higher R^2 value indicates stronger predictive power.
3) Predictive Relevance (Q^2): Measured using Stone-Geisser's Q^2 via the blindfolding procedure. A Q^2 value >0 indicates that the model has predictive relevance (Hair et al., 2017).

3. Statistical Power and Sample Size Justification

This study used 150 respondents, which is considered sufficient for PLS-SEM analysis. Although there is no absolute consensus on the minimum sample size for PLS-SEM, general guidelines suggest that sample size depends on model complexity, desired statistical power, and expected effect size. Based on G*Power analysis (Erdfelder et al., 2009) and PLS-SEM best practices, a sample size of 150 is adequate to detect moderate to large effects ($\beta \geq 0.20$) with a statistical power of 0.80 and a significance level of ($\alpha = 0.05$), particularly in social science models. Additionally, the "10-times rule" (Hair et al., 2017) was met, where the minimum sample size should be 10 times the largest number of structural paths pointing to a single construct. With 6 hypotheses in this model, a sample of 150 respondents ensures a high probability of detecting significant effects, thereby enhancing the reliability and generalizability of the findings.

RESULTS AND DISCUSSION

The findings presented in this section are based on rigorous data analysis, including the evaluation of measurement models, reliability tests, and validity assessments. These analyses are essential in understanding the dynamics of AI adoption among Islamic Religious Education teachers. The following section will provide a detailed description of the research data, which includes the demographic information of the respondents, the variables measured, and the statistical methods used to assess the relationship between the key factors identified in the study.

Description of Research Data

The study begins with a detailed examination of the demographic data of the respondents. This includes key characteristics such as gender, educational background, and years of teaching experience, all of which are essential in understanding the context in which IRE teachers engage with AI technology. By categorizing the respondents based on these variables, the research aims to identify patterns and trends that may influence their behavioral intentions and their readiness to incorporate AI into their classrooms. An overview of the demographic details of the study participants is presented in Table 2.

Table 2. Respondent data

Variable	Demographic	Frequency (N-1719)	Percentage
Gender	Man	95	63.2%
	Woman	55	36.8%
	Total	150	100%
Last education	S1	138	92%
	S2	12	8%
	S3	0	0%
	Total	150	100%
Learning experience	0-5 years	57	38%
	5-10 years	54	36%
	10-15 years	35	23%
	More than 15 years	4	3%
	Total	150	100%

Based on the sample demographic data Table provided, the majority of respondents in this sample were men, accounting for 63.2%, while 36.8% of respondents were female. For the final level of education, the majority of respondents have a bachelor's degree (92%), while only 8% have a master's degree, and no respondents have a doctoral degree. Regarding learning experience, 38% of respondents had learning experience between 0-5 years, 36% between 5-10 years, 23% had 10-15 years of experience, and only 3% had more than 15 years of learning experience.

Measurement Model

The measurement model refers to the four measurements suggested by (Hair & Alamer, 2022), the measurement model refers to the measurement reliability procedure and its validity, while the three measurements are 1) indicator loading and internal consistency reliability, 2) convergent validity, and 3) discriminant validity

Indicator Loading and Internal Consistency Reliability

In finding indicators and reliability according to the PLS-SEM results used for indicator loading in this research. For most items the recommended loading value is >0.708. Table 3 shows the details of the reinforcement, after going through data processing from the algorithm process in PLSM, there are two indicators, namely subjective norms (subnorm 1) and Perceived Behavioral Control (PBC 5) that must be removed, because according to Hair et al. (2019) two indicators that must be removed, because they obtained a loading <0.708. Therefore, there are still twenty-five indicators still used for the next step in the PLS-SEM analysis. Statistical consistency across all indicators in evaluation findings is used for internal consistency reliability. Internal consistency reliability must be reported in several ways, namely Cronbach's Alpha (α) and composite reliability (CR) a must be >0.700 and CR must be >0.708 (Hair et al., 2017). Table 3 shows the details of the Cronbach's Alpha and composite reliability measurement values. The α and CR values for all constructs show good internal consistency, with reliability ranging from 0.771 to 0.889 for α and 0.892 to 0.977 for CR.

Table 3. Loadings of reflective indicators and internal consistency reliability

	Item	Loading	α	CR	AVE	VIF
Attitude	attitude 1	0.800	0.922	0.938	0.683	2.618
	attitude 2	0.777				2.059
	attitude 3	0.886				3.567
	attitude 4	0.836				2.598
	attitude 5	0.771				2.154
	attitude 6	0.815				2.416
	attitude 7	0.892				4.391
Perceived Behavioral Control	pbc 1	0.802	0.872	0.892	0.624	2.198
	pbc 2	0.825				2.002
	pbc 3	0.869				3.384
	pbc 4	0.751				2.395
Subjective Norms	subnorm 2	0.829	0.915	0.893	0.629	2.411
	subnorm 3	0.909				5.093
	subnorm 4	0.852				4.203
	subnorm 5	0.712				1.405
Behavioral Intention	once 1	0.750	0.848	0.907	0.660	1.710
	once 2	0.805				2.046
	once 3	0.844				2.083
	once 4	0.821				1.958
	once 5	0.839				2.251
Behavior	behav 1	0.801	0.853	0.937	0.747	2.104
	behav 2	0.885				3.156
	behav 3	0.872				2.822
	behav 4	0.865				4.064
	behav 5	0.896				4.746

Convergent Validity

Convergent validity has a purpose to know the validity of each relationship between indicators and their latent constructs or variables, statistical issues related to construct validity. Convergent validity suggests that assessments that have similar or similar constructs should have a high correlation.

Regarding convergent validity, AVE scores should be reported. In calculating scores, the PLS-SEM algorithm in SmartPLS is used. The AVE score must be greater than 0.500, this explains 50% or more of the variance. All constructs had AVE scores above 0.500 which explained more than 50% of the variance (Table 3).

Discriminant Validity

Discriminant validity is a validity that looks at the extent to which a construct is different from other constructs. The AVE score of a construct must be lower than the shared variance for all model constructs, this is based on the Fornell Larcker criteria. Then from the research results, it can be seen in Table 4 that the AVE score for each construct is lower than the shared variance score, therefore discriminant validity can be determined based on the Fornell Larker criteria evaluation Then, discriminant validity can also be determined in the form of evaluation through cross-loading.

Table 4. Fornell-larcker

	Attitude	Behavior Intention	Behavior	Perceived Behavioral Control	Subjective Norms
Attitude	0.827				
Perceived Behavioral Control	0.571	0.813			
Subjective Norms	0.787	0.756	0.864		
Behavior Intention	0.656	0.772	0.798	0.790	
Behavior	0.449	0.612	0.528	0.523	0.793

Discriminant validity will emerge if the loading value on one construct is greater than all the cross-loading values on other constructs. As seen in Table 5, all indicator values of the external loadings of each construct are above the values of all cross-loadings on the other constructs.

Table 5. Cross loading

	Attitude	Behavior Intention	Behavior	Perceived Behavioral Control	Subjective Norms
Attitude 1	0.800	0.454	0.628	0.491	0.394
Attitude 2	0.777	0.385	0.679	0.514	0.285
Attitude 3	0.886	0.538	0.722	0.602	0.459
Attitude 4	0.836	0.511	0.658	0.582	0.365
Attitude 5	0.771	0.488	0.567	0.578	0.298
Attitude 6	0.815	0.410	0.625	0.499	0.357
Attitude 7	0.892	0.507	0.667	0.525	0.422
Behav 1	0.750	0.648	0.801	0.628	0.450
Behav 2	0.667	0.599	0.885	0.644	0.489
Behav 3	0.654	0.646	0.872	0.722	0.462
Behav 4	0.658	0.666	0.865	0.726	0.436
Behav 5	0.669	0.700	0.896	0.722	0.444
Once 1	0.427	0.750	0.449	0.480	0.525
Once 2	0.361	0.805	0.559	0.602	0.385
Once 3	0.570	0.844	0.718	0.715	0.645
Once 4	0.631	0.821	0.680	0.690	0.396
Once 5	0.289	0.839	0.614	0.608	0.522
PBC 1	0.600	0.638	0.732	0.802	0.380
PBC 2	0.726	0.625	0.683	0.825	0.495
PBC 3	0.476	0.605	0.628	0.869	0.327
PBC 4	0.360	0.475	0.495	0.751	0.403

	Attitude	Behavior Intention	Behavior	Perceived Behavioral Control	Subjective Norms
PBC 5	0.374	0.672	0.567	0.690	0.458
Subnorm 1	0.241	0.230	0.260	0.197	0.630
Subnorm 2	0.375	0.484	0.426	0.366	0.829
Subnorm 3	0.394	0.472	0.434	0.405	0.909
Subnorm 4	0.445	0.460	0.485	0.405	0.852
Subnorm 5	0.297	0.622	0.421	0.559	0.712

Meanwhile, Table 6 shows that all HTMT values are lower than 0.900, which means that the results have discriminant value, because discriminant validity problems will also arise if HTMT is higher than 0.900, which means it has no discriminant value.

Table 6. HTMT

	Attitude	Behavior Intention	Behavior	Perceived Behavioral Control	Subjective Norms
Attitude					
Perceived Behavioral Control	0.624				
Subjective Norms	0.856	0.831			
Behavior Intention	0.728	0.877	0.894		
Behavior	0.496	0.659	0.579	0.572	

R Square

R Square is a value that explains how much influence the independent (exogenous) variable has on the dependent (endogenous) variable. The value of this effect or influence ranges from 0 to 1. Values of 0.75, 0.50, and 0.25 respectively describe substantial, moderate or weak levels of accuracy (Hair et al., 2014). In this research, it is known that innovative behavior and job performance act as dependent variables. The R Square behavior Intention data obtained was 0.658 or 65.8% of the behavioral Intention variable can be explained by the variables perceived behavioral control and subjective norms. Meanwhile, R Square behavior is 0.789 or 78.9% of behavior variables can be explained by attitude, behavior intention and perceived behavioral control variables. These results fall into the large/substantial category.

Table 7. R square (R^2)

	R Square	R Square Adjusted
Behavior Intention	0.658	0.641
Behavior	0.789	0.779

F Square

The F Square value is used to measure changes in the R Square value if one particular variable is removed from the model with the aim of finding out whether the omitted variable has a substantive impact on the dependent (endogenous) variable. An F Square value of 0.02 includes a small effect, 0.15 includes a medium effect, and 0.35 includes a large effect (Hair & Alamer, 2022). Based on Table 8, it is known that the ability of the attitude variable in explaining is not able to influence the behavior intention variable ($F^2 = 0.006$) and behavior ($F^2 = 0.495$) is relatively large. The ability of perceived behavioral control to explain behavioral intention is relatively large ($F^2 = 0.505$) and to behavior ($F^2 = 0.143$) is relatively small. The ability of subjective norms variables to explain behavioral intention is relatively small ($F^2 = 0.159$).

Table 8. F square (F^2)

	Attitude	Behavior Intention	Behavior	Perceived Behavioral Control	Subjective Norms
Attitude		0.006	0.495		
Behavior Intention			0.145		
Behavior					
Perceived Behavioral Control		0.505	0.143		
Subjective Norms		0.159			

Q Square

In the Table it can be seen that the model behave 3 shows relatively good performance with RMSE values of 0.477, MAE 0.326 and MAPE 8.527% and Q^2 of 0.530. This shows that this model has fairly accurate predictions and behavior model 3 can explain most of the variability in the data, but it is variable behave 2 shows slightly lower performance with RMSE values of 0.509, MAE 0.396, and MAPE 10.504% and Q^2 0.4076, from this data it can be said that behavior 2 shows there is room for improvement, this variable is still quite good but shows slightly worse performance compared to the variable behave 3

Overall the behavior variable shows quite consistent results in terms of RMSE and MAE, although there are small differences in the values between the variables. Then meanwhile, variable Once 3 shows the best value with RMSE 0.361 and MAPE 7.071% and Q^2 0.574, which means this model is better at predicting with high accuracy and can explain data variability, but the variable Once 1 shows lower results in Q^2 (0.276), which indicates that this model is less effective in describing variability in the data. If we look at the existing metrics, the model Once 3 seems to be the best in terms of data accuracy and explain ability, while the model Behave 2 And Once 5 has slightly lower performance and shows potential for further improvement.

Table 9. Q square (Q^2)

	RMSE	THERE IS	MAP	Q^2 Predict
Behave 3	0.477	0.326	8.527	0.530
Behave 2	0.509	0.396	10.504	0.476
Behave 1	0.409	0.309	7.457	0.544
Behave 5	0.499	0.365	9.551	0.532
Behave 4	0.474	0.370	9.749	0.533
Once 2	0.502	0.339	9.398	0.288
Once 3	0.361	0.291	7.071	0.574
Once 1	0.455	0.371	8.460	0.276
Once 4	0.456	0.358	8.568	0.406
Once 5	0.549	0.401	10.578	0.341

Based on the measurement model, this research assesses several factors that influence the behavioral intentions and behavior of Islamic teachers in utilization AI in the learning process, the perceived behavioral control variable is a variable that reflects the perceptions of Islamic religious teachers regarding the ability of Islamic religious teachers to be able to access AI and leverage AI teaching in the learning process. The perceived behavioral control variable was the most significant variable in predicting behavioral intentions and usage-related behavior AI, perceived behavioral control is the strongest predictor of behavioral intention (Lung-Guang, 2019) but according to Teo & van Schaik (2012), reported that no influence was found between perceived behavioral control and a person's behavioral intention to do something. The subjective norm variable is a variable that provides an overview of Islamic religious teachers, elements such as teachers and families of students and families of Islamic religious teachers who support the use of AI to support the learning process is the second important factor after perceived behavioral control, according to (Cirignano, 2023). Subjective norms are a strong predictor of the intention or actual use of technology in the TPB framework in the teaching and learning process. Therefore, it is true that the use of AI by Islamic religious teachers is significantly predicted by the influence of the environment around them. Furthermore, the research results show that the attitude variable has a significant relationship with behavioral intentions related to use AI by Islamic teachers in the learning process. According to Teo & van Schaik (2012) found research results that a positive attitude is the strongest predictor of the use of something from behavioral intentions and behavior itself. However, the results of other research show that attitudes are not significantly related to behavioral intentions and behavior (Cirignano, 2023).

Table 10. Results data

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
Attitude -> Behavior Intention	0.062	0.063	0.151	0.411	0.681
Attitude -> Behavior	0.432	0.438	0.113	3.825	0.000
Behavior Intention -> Behavior	0.278	0.279	0.129	2.149	0.032
Perceived Behavioral Control -> Behavior Intention	0.586	0.570	0.116	5.032	0.000
Perceived Behavioral Control -> Behavior	0.300	0.289	0.129	2.315	0.021
Subjective Norms -> Behavior Intention	0.278	0.291	0.086	3.235	0.001

The research results in Table 10, show the relationships between factors in the theory of planned behavior, such as attitudes, perceived behavioral control, subjective norms of behavioral intentions and behavior itself, each row in Table 9 indicates the relationship between two variables which include several statistical measures, including the relationship coefficient (original sample), sample mean value, standard deviation, T statistic value and P value. The relationship between the attitude variable and behavioral intention is 0.062, which is very small, close to zero, the T statistic value is 0.411 which indicates a relationship that is not statistically significant (P = 0.681), because the P value is greater than 0.05, this shows that attitude does not have a significant influence on behavioral intention in this sample.

Then, the relationship between the attitude variable and the behavioral variable shows a coefficient of 0.432 with a high value on the T statistic of 3.825 with a very low P value, namely P = 0.000. This result shows that attitude has a positive influence on behavior. This result shows that the more positive a person's attitude is, the more likely they are to carry out the relevant behavior. The next result is that the coefficient of the relationship between behavioral intentions and behavior is 0.278, with a T statistic value of 2.149 and a P value = 0.032, because the P value is smaller than 0.05, this relationship is considered statistically significant, this result shows that behavioral intentions influence behavior. Then the relationship between perceived behavioral control and behavioral intention has a coefficient of 0.586, with a very high T statistic of 5.032 and a very low P of 0.000. This shows that perceived behavioral control has a very strong and significant influence on behavioral intentions.

The next coefficient result is that the coefficient of the relationship between perceived behavioral control and behavior is 0.300, with a T statistical value of 2.315 and a P value of 0.021. Since the P value is less than 0.05, this relationship is also statistically significant. This suggests that perceived behavioral control contributes to individuals' actual actions. Then the relationship between subjective norms and behavioral intentions has a coefficient of 0.278 with a statistical value of P = 0.001. These results show that subjective norms have a significant influence on behavioral intentions.

It can be said that the stronger the perceived social norms, the greater the possibility that individuals will intend to carry out certain behavior.

Overall, these results show that factors relating to attitudes, perceived behavioral control, and subjective norms have a significant influence on individual intentions and behavior. Perceived behavioral control, in particular, shows a very strong influence on both behavioral intentions and actual behavior. In contrast, attitudes have a significant influence on behavior, but not on behavioral intentions, which may indicate that other factors such as intention and control are more dominant in predicting actions.

The findings of this study reveal both consistencies and divergences from previous research on technology adoption, particularly within educational contexts. The significant influence of PBC on intention and behavior aligns with earlier studies that emphasize the importance of self-efficacy and resource availability in the process of technology integration (Habibi et al., 2023). This suggests a generalizable principle: individuals are more likely to adopt new technologies when they feel competent and adequately supported by their environment or available resources.

Furthermore, the finding regarding the significant influence of subjective norms on intention also supports existing literature that highlights the role of social pressure in professional settings. This implies that strengthening learning communities and leadership roles that encourage the use of AI can enhance the readiness of Islamic Education teachers to adopt such technologies. These results reinforce the application of the TPB within collectivist cultural contexts, where social expectations often exert a greater influence than individual attitudes.

However, the result indicating that Attitude does not significantly affect intention represents a notable deviation from the typical TPB model. According to TPB, attitudes toward behavior are generally regarded as a key predictor of intention. Yet, within the context of Islamic Religious Education teachers, this finding suggests that personal beliefs or internal attitudes may not be sufficient to form an intention to adopt AI. This may be attributed to the distinctive nature of Islamic education, where collective norms or PBC tend to play a more decisive role than individual attitudes.

The most striking finding is the non-significant relationship between Behavioral Intention and Actual Behavior, accompanied by evidence of a direct influence of both Attitude and PBC on behavior. This challenges the sequential model of TPB, where intention is expected to act as the main mediator between attitude and behavior. In this context, it is possible that Islamic Religious Education teachers adopt AI technologies due to:

1. Direct positive attitudes, even in the absence of a clearly formed or structured intention. This may reflect spontaneous adoption driven by curiosity or the immediate perceived benefits of the technology.
2. Perceived ability and opportunity (PBC), enabling teachers to use AI without necessarily undergoing a deliberate intention-formation process.

The phenomenon known as the intention-behavior gap (Sheeran, 2002) is well-documented in behavioral research. This implies that although teachers may intend to use AI, its actual implementation is often hindered by practical constraints or is instead driven by more immediate enabling factors such as PBC or personal dispositions like strong attitudes bypassing the intentional stage altogether.
Therefore, effective intervention strategies should not only aim to foster intention but also focus on facilitating actual behavioral execution through the provision of practical support and access to enabling resources.

This study offers a significant contribution by being one of the pioneering investigations to comprehensively examine the determinants of AI adoption among Islamic Religious Education teachers in Indonesia, specifically in Tanjung Jabung Barat Regency, Jambi Province, using the TPB framework. While educational technology adoption has been widely studied, limited attention has been given to the psychosocial factors underlying the acceptance and use of AI by Islamic Religious Education teachers, particularly through a behavioral theory lens. This study addresses that gap by presenting TPB-based empirical evidence within a distinct cultural and educational context, thereby providing novel insights into the dynamics of AI adoption among Islamic education teachers.

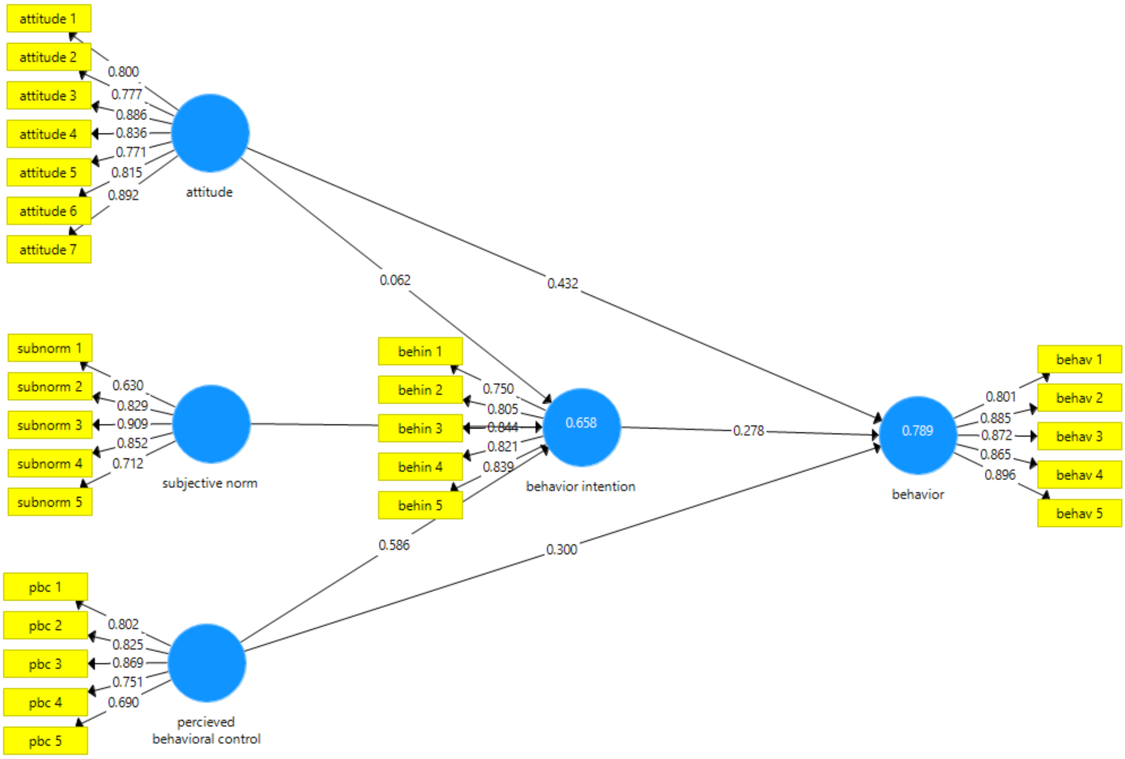

Figure 3. Final Model

The findings of this research hold important implications for stakeholders in Islamic education. The result that perceived behavioral control is the strongest predictor of both the intention and actual behavior to adopt AI highlights the need for practical interventions such as hands-on training and the creation of supportive environments to enhance teachers' confidence and ability to utilize AI tools. Furthermore, the significant influence of subjective norms emphasizes the importance of support from colleagues, school leaders, and the broader community in encouraging adoption. These insights may guide policymakers and technology developers in designing more effective training programs and adequate infrastructure. Nevertheless, this study is not without limitations. First, the quantitative survey approach may not fully capture the complexity of teachers' experiences in adopting AI; qualitative or mixed-method approaches could offer deeper understanding. Second, the geographical focus on a single region limits the generalizability of the findings to the broader population of Islamic Religious Education teachers across Indonesia. Third, although TPB demonstrated strong explanatory power, other influential variables such as demographic factors or more specific technological infrastructure might have been overlooked in this model.

CONCLUSION

This study aimed to analyze the behavioral factors influencing the intention and actual behavior of Islamic Religious Education teachers in adopting AI within 21st-century learning, using the TPB framework. The findings identified PBC as the most influential factor, significantly predicting both intention (coefficient = 0.586, $p < 0.001$) and behavior (coefficient = 0.300, $p = 0.021$). Subjective norms also demonstrated a significant impact on intention (coefficient = 0.278, $p = 0.001$), while attitude had no significant effect on intention ($p = 0.681$) but did significantly influence actual behavior (coefficient = 0.432, $p < 0.001$). These results confirm the applicability of TPB in understanding technology adoption among Islamic Religious Education teachers, with the model explaining 65.8% of the variance in intention and 78.9% of the variance in behavior. The identification of an intention-behavior gap also suggests that teachers' actions are more likely driven by situational enablers and personal efficacy rather than structured intention, indicating a deviation from the linear structure of TPB.

Based on these insights, it is recommended that future interventions go beyond merely shaping teacher attitudes and focus on enhancing their perceived control by improving access to technological resources, offering targeted professional development, and cultivating a supportive school environment. Future research should consider the use of qualitative or mixed-method approaches to uncover deeper contextual and emotional factors that may mediate or moderate AI adoption among teachers. Exploring potential mediating variables, particularly in the relationship between attitude and intention, may provide further clarity. Additionally, expanding the research across different geographic regions and educational levels can enrich our understanding of AI adoption dynamics in broader Islamic educational contexts.

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