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Analyzing Intentions to Adopt Artificial Intelligence in Islamic Education Practices

Menganalisis Niat Penerapan Kecerdasan Buatan dalam Praktik Pendidikan Islam

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Abstract: *This research explored the key factors shaping the adoption of artificial intelligence (AI) in Islamic studies education, employing the Technology Acceptance Model (TAM) as the guiding framework. A quantitative approach was adopted, with data collected from 255 participants through an online survey distributed via Google Forms. The reliability and validity of the survey instrument were rigorously tested. Data was analyzed using Structural Equation Modeling (SEM) with Smart PLS software. The findings revealed that Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) significantly influence educators' attitudes toward using AI in Islamic education. Notably, PEOU emerged as a stronger determinant of attitude, highlighting the importance of user-friendly technologies in fostering acceptance. Furthermore, the study established a clear link between positive attitudes toward AI and Behavioral Intention (BI) to adopt the technology, which drives actual usage. These results underscore the critical role of simplifying technology to encourage its adoption and suggest practical pathways for integrating AI into Islamic studies teaching and learning.*
Keywords: Artificial intelligence (AI); Technology acceptance model (TAM); Islamic study

Abstrak: Penelitian ini mengeksplorasi faktor-faktor utama yang memengaruhi adopsi kecerdasan buatan (AI) dalam pendidikan studi Islam, dengan menggunakan kerangka kerja Technology Acceptance Model (TAM). Penelitian ini menggunakan pendekatan kuantitatif, dengan mengumpulkan data dari 255 responden melalui survei online yang menggunakan Google Forms. Instrumen survei telah diuji validitas dan reliabilitasnya secara ketat. Analisis data dilakukan menggunakan metode Structural Equation Modeling (SEM) dengan bantuan perangkat lunak Smart PLS. Hasil penelitian menunjukkan bahwa kegunaan yang dirasakan (Perceived Usefulness -PU) dan kemudahan kegunaan yang dirasakan (Perceived Ease of Use-PEOU) secara signifikan memengaruhi sikap pendidik terhadap penggunaan AI dalam pendidikan studi Islam. PEOU memiliki pengaruh yang lebih besar terhadap sikap, yang menekankan pentingnya teknologi yang mudah digunakan untuk meningkatkan penerimaan. Selain itu, penelitian ini juga mengungkapkan bahwa sikap positif terhadap AI secara langsung berkaitan dengan niat perilaku (Behavioral Intention - BI) untuk mengadopsi teknologi tersebut, yang pada akhirnya mendorong penggunaan aktual. Temuan ini menegaskan pentingnya menyederhanakan penggunaan teknologi untuk mendorong adopsi, dan memberikan arahan praktis untuk mengintegrasikan AI ke dalam proses pengajaran dan pembelajaran studi Islam.
Kata-kata kunci: *Artificial intelligence (AI); Technology acceptance model (TAM); Studi Islam*

Introduction

Industrial Revolution 4.0 has brought changes in the rapid development of digital technology, one of which is Artificial Intelligence (AI) technology. AI is a simulation of human intelligence, modelled in machines and programmed to think like humans. The application of AI has penetrated all aspects, such as technology, industry, medicine, business, and education (Holmes et al., 2019; Prahani et al., 2022). In the education sector, AI can potentially transform the teaching-learning process. However, the use of AI in

education is a topic of debate. Proponents argue that AI can personalize learning, automate routine tasks, improve feedback loops, and provide targeted interventions, ultimately improving learning outcomes (Cardona et al., 2023; Seo et al., 2021). However, critics express concerns that the use of AI in education may limit students' ability to develop critical thinking and self-learning skills. There are also ethical and practical considerations, such as ensuring transparency and fairness of AI systems, addressing potential biases, and preventing misuse, including issues related to plagiarism and cheating (Cardona et al., 2023).

Despite the debate, AI can provide positive change in education, and it is essential to approach integration wisely and responsibly to maximize its potential benefits. According to Tlili (2023). The discourse on the use of AI in education has yielded positive results. Instead of some drawbacks, educational practitioners are looking for the right way to implement AI and focusing on maximizing the benefits of its use. The study by Tlil (2023) shows that this technology can be a promising alternative to education. However, there is still a need for caution and guidance when implementing it in the classroom.

Before implementing AI in the classroom, it is essential to understand the intention and readiness of lecturers and students to adopt AI in the teaching and learning process. It is necessary because investigating the intention to embrace AI in education helps identify factors that influence AI adoption to design effective strategies for AI integration, overcome potential barriers to AI adoption, and help educators and policymakers maximize AI's potential benefits in the teaching and learning process. It can help ensure that AI adoption is aligned with teaching and learning objectives and implemented in a way that maximizes its potential benefits (Nja et al., 2023a; Roy et al., 2022; Wang Youmei et al., 2021). Studies have discussed teachers' intentions to implement AI in the classroom. Among them are Ayanwale et al. (2022), who examined teacher intentions and readiness to teach using AI at the elementary school level. Nja (2023) examined teachers' intentions to adopt AI for natural science learning. Zhang (2023) in his research, he discussed prospective teachers' acceptance of AI. No research has been found from the existing literature investigating the intention and readiness of lecturers and students to adopt AI within the Faculty of Islamic Studies.

The novelty of this research lies in its focus on exploring the intentions and readiness of both lecturers and students to adopt AI specifically within the context of the Faculty of Islamic Studies at Kalimantan Arsyad Al Banjari University. Unlike the existing literature, which predominantly centers on primary education or specific subjects like natural sciences, this study offers a unique contribution by examining the integration of AI in an Islamic educational environment. It addresses the dual perspective of both lecturers and students, providing a more comprehensive understanding of AI adoption within a specialized academic domain. Additionally, the context of Kalimantan Arsyad Al Banjari University adds further significance, as no previous research has explored AI acceptance and readiness in this particular setting. By doing so, the study enriches the knowledge on technology acceptance in higher education and aligns with the growing global discourse on AI integration in diverse academic fields, including religious and humanities-oriented faculties.

Several studies discuss the integration of AI in education. Research conducted by Chiu et al. (2023), Su et al. (2023), Dakakni & Safa, (2023) highlight the opportunities, challenges,

and recommendations for future research on the application of AI in education. In education, AI can assign tasks based on individual competencies, provide conversations between humans and machines, analyze student work for feedback, and improve adaptability and interactivity in digital environments. AI also has the opportunity to provide adaptive teaching strategies, improve teachers' ability to teach, support teachers' professional development, and support teachers' work in assessment by providing automated scoring and predicting student performance. As for the challenges of AI implementation in education, teachers lack knowledge, skills, and confidence about AI, curriculum design, and teaching guidelines.

Other research highlights the factors influencing teachers' adoption of AI in education. The factors impacting teachers' intention to learn how to use AI-based applications in their teaching were investigated by Wang Youmei et al. (2021). Making it easier for educators to incorporate AI technology into their lessons can also increase the perceived value of AI-assisted instruction and encourage teachers to use it. Apart from enhancing the AI technology's user interface, several studies have demonstrated that instructors' readiness to integrate AI technology into their lesson plans can be influenced by their level of confidence and proficiency with the technology.

Ayanwale et al. (2022) examined teachers' readiness and intention to teach using AI in primary schools. The results showed confidence in teaching AI predicted intention to teach, and AI relevance strongly predicted teaching readiness. While other characteristics influenced AI teaching, anxiety and social kindness did not predict teachers' intention or willingness to integrate AI in the classroom. Furthermore, research conducted by Nja et al. (2023) showed that this study found that self-esteem, expected benefits, simplicity of use, and views on the technology mainly influenced teachers' intention to use AI. The results suggest that teachers may put little effort into using AI in the classroom, but having control over their essential skills can improve attitudes and correct behavioural intentions. The study found that AI adoption depends on its ease of use. Students' interest in AI stems from the potential benefits that the technology can provide in the classroom. From the existing research, few studies investigate teachers' and students' interest in adopting AI in the teaching and learning process in the Islamic studies environment. For this reason, this research was conducted to add to the literature related to teachers' and students' interest in adopting AI in the context of Islamic studies.

In recent years, significant research has been conducted on user acceptance of technologies that people can use. The TAM model explains user behaviour and predicts underlying factors. Davis introduced this model (1989), who stated that the acceptance of new technology depends on three factors: perceived usefulness (PU), perceived ease of use (PEOU), and attitude toward using (ATU). TAM proposes that perceived usefulness, simplicity of use, and attitude toward use can be used to determine users' behavioural intentions. Its popularity has grown mainly due to its flexibility in various settings and samples. Granić & Marangunić (2019) and Scherer et al. (2019) provide concrete examples of teachers' willingness to adopt technology in their classrooms.

Perceived usefulness (PU) is the extent to which a user believes using a given system will improve job performance. TAM predicts that PU will influence ATU and BI. Previous research shows that PU has a sizable impact on attitudes toward system use (Al-Hattami, 2023). EOU is the extent to which users believe using a particular technology will require

less effort (Davis, 1989a). TAM predicts that EOU will impact ATU. According to Fathema et al. (2015). The impact and link are as follows: customers view a technology as applicable when they find it easy to use. If the technology is simple to use, people will be more upbeat. In earlier studies on technology-assisted education, this effect and connection were emphasized (Al-Hattami, 2023).

Attitude toward Using (ATU) reveals whether a teacher is for or against using IT in the classroom. TAM expects that ATU will impact BI. Previous research also shows that ATU impacts AU (Lawrence & Tar, 2018). Fathema et al. (2015) summarized this impact/relationship by stating that consumers intend to use technology and will do so if they have a positive attitude towards the technology. Previous research has empirically demonstrated this impact/relationship (Weng et al., 2018).

Behavioural intention (BI) refers to a user's willingness to utilize and desire to continue using a particular technology. Huwaida et al. (2023) found that behavioural intentions affect actual usage when adopting technology. Based on this investigation, the study's model is shown in Figure 1 and establishes the following hypotheses:

H1: PU strongly affects ATU's adoption of AI in Islamic education studies.
H2: EOU increases ATU to adopt AI in Islamic education studies.
H3: ATU positively increases the interest in AI integration for Islamic education studies.
H4: BI positively impacts AU's adoption of AI in Islamic education studies.

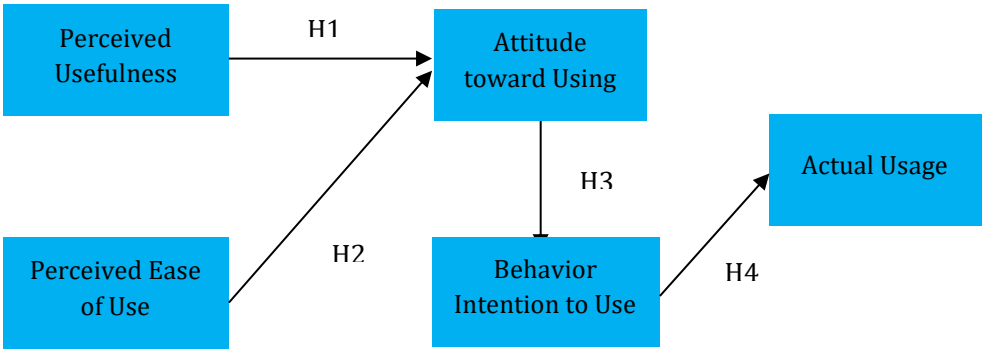

Figure 1. Research Model

Method

This research will utilize a quantitative approach. This method allows researchers to model and test relationships between variables and generate an in-depth understanding of the factors influencing AI adoption in the context of Islamic education at UNISKA (Ary et al., 2010; Creswell, 2014). This study's population consisted of lecturers and students from UNISKA's Faculty of Islamic Studies. The samples totaled 255 Faculty of Islamic Studies UNISKA students and teachers. The researcher used purposive sampling, where the samples selected were lecturers and students who were likely to or had already used AI in the teaching and learning process.

This research refers to the Technology Acceptance Model (TAM). TAM posits that user acceptance is influenced by two key variables: perceived usefulness (PU) and perceived ease of use (EOU). Perceived usefulness refers to the extent to which a user believes that using a particular technology will enhance their performance, while perceived ease of use indicates the degree to which the user finds the technology effortless to operate. These

variables significantly impact the user's attitude toward using the technology (ATU), subsequently influencing their behavioral intention (BI) to use it (Davis, 1989a).

This research begins with conducting pre-research, identifying literature and conceptual frameworks, and developing research instruments, such as questionnaires. Furthermore, the research implementation stage involves collecting data from respondents through an online survey (Google Form) and verifying the validity and reliability of the instrument using Smart PLS. After the data is collected, the next stage is data analysis using Structural Equation Modeling (SEM) with Smart PLS. The last stage is data interpretation and preparation of research reports.

Result and Discussion

Respondents' Profile

Two hundred fifty-five respondents are participating in this study. Table 1 shows the respondents' profiles, including their gender, age, occupation, and study program.

Table 1. Respondents' Profile (N= 255)

Question	Categories	N	%
Gender	Male	69	27.05
	Female	186	72.95
Age	< 20	86	33.73
	21-25	136	53.33
	26-30	14	5.49
	31-35	8	3.14
	>36	11	4.31
Occupation	Teacher	15	5.88
	Student	240	94.12
Study Program	Ekonomi Syariah	35	13.72
	Hukum Ekonomi Islam	43	16.86
	Pendidikan Guru Agama Islam	160	62.75
	Other	17	6.67

Measurement Model

Figure 2 and Table 2 show the results of the convergent validity and reliability tests, which demonstrate that all constructs—perceived Usefulness (PU), Perceived Ease of Use (PEOU), Attitude Toward Using (ATU), Behavioral Intention (BI), and Actual Use (AU)—exhibit strong psychometric properties. The factor loadings for each item across all constructs exceed the acceptable threshold of 0.7, indicating that the items are well-correlated with their respective constructs. Additionally, the Cronbach's Alpha (CA) and Composite Reliability (CR) values are above the recommended 0.7 level, with some constructs exceeding 0.9, highlighting excellent internal consistency. It means that the constructs are reliably measured, and the items within each construct consistently reflect the underlying factor. Moreover, the Average Variance Extracted (AVE) values for all constructs are above 0.5, most significantly exceeding this threshold. It further supports the convergent validity, indicating that the constructs explain more than half of the variance in

their corresponding items. Given these results, the constructs can be considered reliable and valid for further testing in structural equation modeling (SEM) or other advanced statistical analyses. Therefore, the measurement model is robust and appropriate for proceeding with the following stages of hypothesis testing and model validation.

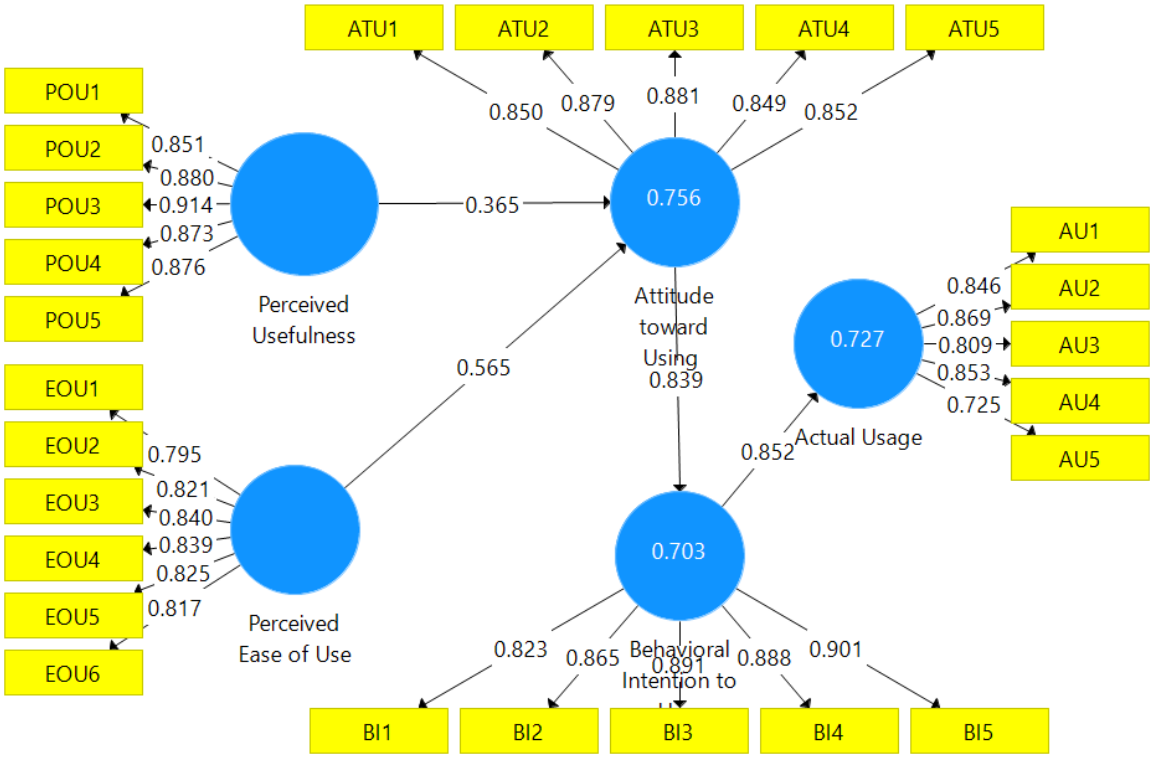

Figure 2. PLS Algorithm result

Table 2. Reliability and Convergent Validity

Factor	Item	Loading	CA	CR	AVE
POU	POU1	0.851	0.926	0.944	0.772
	POU2	0.880			
	POU3	0.914			
	POU4	0.873			
	POU5	0.876			
EOU	EOU1	0.795	0.905	0.926	0.677
	EOU2	0.821			
	EOU3	0.840			
	EOU4	0.839			
	EOU5	0.825			
	EOU6	0.817			
ATU	ATU1	0.850	0.914	0.935	0.743
	ATU2	0.879			
	ATU3	0.881			
	ATU4	0.849			

	ATU5	0.852			
BI	BI1	0.823	0.922	0.942	0.764
	BI2	0.865			
	BI3	0.891			
	BI4	0.888			
	BI5	0.901			
AU	AU1	0.846	0.879	0.912	0.676
	AU2	0.869			
	AU3	0.809			
	AU4	0.853			
	AU5	0.725			

The discriminant validity results in Table 3, based on the Fornell-Larcker criterion, indicate that all constructs meet the requirements for discriminant validity. It is shown that the square root of the Average Variance Extracted (AVE) for each construct (bolded diagonal values) is higher than the correlations with any other construct in the model. For instance, the square root of AVE for Actual Use (AU) is 0.822, which is greater than its correlations with other constructs like ATU (0.786) and BI (0.852). Similarly, all other constructs, including Attitude Toward Using (ATU), Behavioral Intention (BI), Perceived Ease of Use (PEOU), and Perceived Usefulness (PU), follow the same pattern, confirming that each construct is distinct from the others. These findings suggest that the model has adequate discriminant validity, meaning that the constructs measure unique concepts, and the model can proceed to further testing and analysis.

Table 3. Discriminant Validity

Variable	Fornell-Larcker criterion				
	AU	ATU	BI	EOU	EOU
AU	**0.822**				
ATU	0.786	**0.862**			
BI	0.852	0.839	**0.874**		
EOU	0.775	0.834	0.740	**0.823**	
PU	0.714	0.781	0.759	0.736	**0.879**

Table 4. Cross Loading

		AU	ATU	BI	EOU	PU
ATU	ATU1	0.593	**0.850**	0.637	0.718	0.628
	ATU2	0.642	**0.879**	0.702	0.711	0.680
	ATU3	0.675	**0.881**	0.683	0.745	0.666
	ATU4	0.743	**0.849**	0.796	0.725	0.683
	ATU5	0.723	**0.852**	0.782	0.696	0.704
AU	AU1	**0.846**	0.715	0.780	0.711	0.666
	AU2	**0.869**	0.692	0.727	0.657	0.582
	AU3	**0.809**	0.617	0.643	0.638	0.589
	AU4	**0.853**	0.708	0.731	0.663	0.657

	AU5	**0.725**	0.468	0.604	0.499	0.413
BI	BI1	0.726	0.760	**0.823**	0.660	0.702
	BI2	0.716	0.724	**0.865**	0.627	0.648
	BI3	0.714	0.703	**0.891**	0.617	0.670
	BI4	0.786	0.732	**0.888**	0.660	0.650
	BI5	0.778	0.742	**0.901**	0.664	0.644
EOU	EOU1	0.542	0.636	0.539	**0.795**	0.587
	EOU2	0.650	0.649	0.604	**0.821**	0.618
	EOU3	0.625	0.725	0.612	**0.840**	0.617
	EOU4	0.692	0.742	0.676	**0.839**	0.635
	EOU5	0.691	0.691	0.652	**0.825**	0.572
	EOU6	0.622	0.664	0.559	**0.817**	0.606
POU	POU1	0.563	0.617	0.587	0.601	**0.851**
	POU2	0.604	0.656	0.632	0.641	**0.880**
	POU3	0.638	0.702	0.690	0.660	**0.914**
	POU4	0.669	0.758	0.726	0.679	**0.873**
	POU5	0.650	0.685	0.685	0.647	**0.876**

The cross-loading table 4 demonstrates that the items load higher on their respective constructs than on any other, indicating good discriminant validity. For example, ATU1 to ATU5 have higher loadings on the Attitude Toward Using (ATU) construct (ranging from 0.849 to 0.881) compared to their loadings on other constructs, such as AU (0.593 to 0.743) and BI (0.637 to 0.796). Similarly, items in the Actual Use (AU) construct load significantly higher on AU (ranging from 0.725 to 0.869) than on other constructs like ATU or BI. The same pattern is observed for the different constructs, such as Behavioral Intention (BI), Perceived Ease of Use (PEOU), and Perceived Usefulness (PU), where each item loads more heavily on its intended construct. This pattern reinforces the discriminant validity of the model, confirming that the items are measuring distinct constructs and that the model is suitable for further analysis.

Structural Model

The researcher in this study used 500 sub-samples to evaluate the correlations between different paths during the structural stage and test the hypotheses. During this phase, the path coefficient (β), which measures the strength and validity of the link, is tested. A t-value of greater than 1.96 and a p-value of less than 0.05 are necessary for a hypothesis to be accepted (Hair et al., 2017).

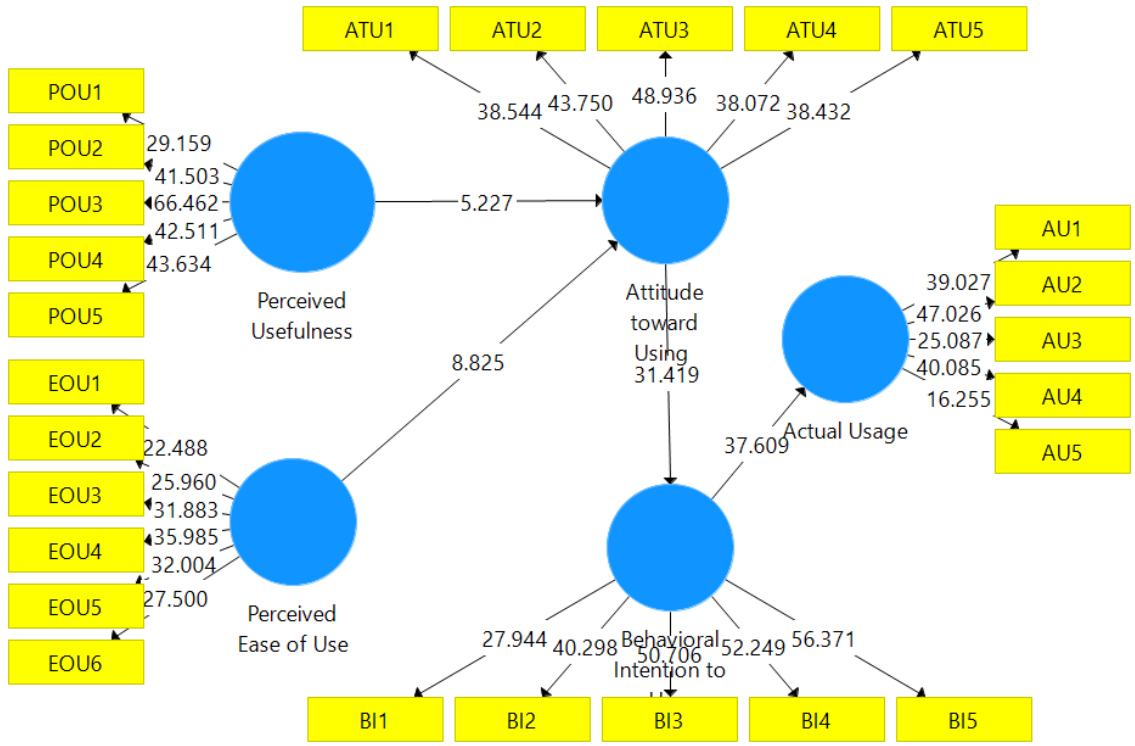

Figure 3. Bootstrapping with 500 sub-samples

Figure 3 and Table 4 display the structural model's computed findings using SmartPLS. The investigators discovered that perceived usefulness and attitude toward the system have a positive and statistically significant relationship. A path coefficient of 0.365 indicates a moderate positive effect, a t-value of 5.227, and a p-value of 0.000. With a path coefficient of 0.565 and a highly significant t-value of 8.825, perceived ease of use has a more robust, favorable, and meaningful effect on attitude toward utilizing the system. With a high path coefficient of 0.839, a t-value of 31.419, and a p-value of 0.000, attitude toward usage has a powerful positive effect on behavioral intention. The strong path coefficient of 0.852, a t-value of 37.609, and a p-value of 0.000 indicate that behavioral intention is a reliable indicator of Actual Usage.

Table 5. Path Analysis

Path	β	t-value	p-value	Supported?
H1: Perceived usefulness - > Attitude toward using	0.365	5.227	0.000	Yes
H2: Perceived ease of use - > Attitude toward using	0.565	8.825	0.000	Yes
H3: Attitude toward using - > Behavioral intention	0.839	31.419	0.000	Yes
H4: Behavioral intention - > Actual Usage	0.852	37.609	0.000	Yes

Hypothesis 1: The Effect of Perceived Usefulness on Attitude Toward Using

The first hypothesis (H1) examines the relationship between Perceived Usefulness and Attitude Toward Using a system. The analysis shows a significant positive effect with a path coefficient (β) of 0.365, a t-value of 5.227, and a p-value of 0.000, confirming the hypothesis. This finding aligns with Nuryakin et al. (2023), who identified perceived usefulness as a critical determinant in shaping users' attitudes toward online learning technology. When users believe a system improves their performance or brings value to their tasks, they are more likely to develop a positive attitude toward using the system. When students or teachers perceive that technology enhances learning or teaching efficiency, their attitude towards adopting the technology improves. Thus, perceived usefulness remains a key factor in technology acceptance.

Several studies in technology acceptance research have supported this connection between perceived usefulness and attitude. For instance, (Moses et al., 2013), in his Technology Acceptance Model (TAM), found that perceived usefulness significantly influences the likelihood of users adopting a laptop. Mosese's research highlights how individuals' belief that a technology will improve their job performance can lead to a more favorable attitude toward its usage. This factor is particularly important in educational contexts because technology can directly enhance learning efficiency, making it easier for teachers to manage tasks and for students to grasp complex concepts, ultimately leading to increased adoption rates.

Further studies have expanded on this relationship. For example, Hart & Laher (2015) confirmed that the perceived usefulness of technology is one of the strongest predictors of user acceptance across various sectors, including education. Their research found that when technology is seen as an effective tool for improving educational outcomes, it fosters positive attitudes toward its use. Similarly, Azman et al. (2020) studied technology adoption among teachers and found that perceived usefulness was a key factor in their willingness to integrate technology into their teaching practices through MYGURU. In the context of online learning, where students and educators rely heavily on digital platforms, the perceived usefulness of these tools becomes even more significant. When both students and teachers view technology as beneficial for improving learning efficiency, their attitude toward using such systems becomes more positive, reinforcing the importance of perceived usefulness in the broader framework of technology acceptance.

Hypothesis 2: The Effect of Perceived Ease of Use on Attitude Toward Using

The second hypothesis (H2) confirms that Perceived Ease of Use significantly influences users' Attitude Toward Using technology, with a β value of 0.565 and a highly significant t-value of 8.825. It suggests that when users find a system easy to navigate and operate, they are more likely to develop favorable attitudes toward using it. This finding aligns with Davis (1989b), who argued that systems perceived as easy to use generally lead to stronger positive attitudes toward adoption. In educational settings, this factor is critical as students and educators are more inclined to adopt technologies that do not require extensive learning or implementation. A user-friendly system lowers the cognitive load and time investment needed to understand it, increasing the likelihood of adoption. The ease of use directly reduces resistance and makes technology more appealing, encouraging widespread acceptance.

Recent studies in the past five years further support this relationship. For example, Teo et al. (2015) examined teachers' attitudes toward educational technology adoption and found that perceived ease of use was a major predictor of positive attitudes. Their research showed that teachers, especially in the context of gender, were more likely to adopt intuitive and easy tools to integrate into their teaching processes. Similarly, Qashou (2021), in their study on mobile learning applications, demonstrated that perceived ease of use significantly impacted users' attitudes, particularly among students in Palestine who were hesitant about adopting the M Learning system. The easier the application was to use, the more likely it was to generate positive attitudes and frequent use. These findings reinforce that technologies designed with simplicity and user-friendliness in mind are more likely to foster positive attitudes and encourage broader adoption in both educational and professional settings.

Hypothesis 3: The Effect of Attitude Toward Using on Behavioral Intention

The third hypothesis (H3) examines the effect of Attitude Toward Using on Behavioral Intention, and the results reveal a powerful relationship with a β value of 0.839, a t-value of 31.419, and a p-value of 0.000. This finding supports the fundamental principles of the Technology Acceptance Model (TAM), as proposed by Davis (1989b), which argues that a positive attitude toward using a system is one of the most powerful predictors of the intention to adopt that technology. The high β value in this study indicates that when users, such as students or educators, have a favorable attitude towards an AI-based system or any educational technology, they are significantly more likely to form an intention to use it consistently. In educational settings, a positive attitude could result from users' experiences of the technology being practical, functional, or aligned with their academic goals. It directly translates into a firm intention to incorporate the technology into their daily learning or teaching practices.

Recent research has further reinforced the importance of attitude in shaping behavioral intentions, especially in educational technology contexts. For instance, Mailizar et al. (2021) found that attitudes toward using educational platforms strongly influenced students' intention to adopt e-learning in mathematics. Similarly, Al-Hamad et al. (2021) explored the factors affecting the intention to use mobile learning systems, and perceived benefits significantly shaped users' behavioral intentions. Another study by De Cosmo et al. (2021), showed that a positive attitude towards using AI-powered teaching tools significantly boosted teachers' intention to use such tools in classrooms. These studies highlight the positive attitudes' consistent role in predicting behavioral intention across various educational technologies, suggesting that fostering favorable attitudes is key to promoting the successful adoption and consistent use of new technological tools in education.

Hypothesis 4: The Effect of Behavioral Intention on Actual Usage

The fourth hypothesis (H4) investigates the relationship between Behavioral Intention and Actual Usage, revealing a highly significant and robust link, with a β value of 0.852, a t-value of 37.609, and a p-value of 0.000. This strong association confirms that when users express a clear intention to use a technology, this intention is likely to manifest as actual system usage. It aligns with the Technology Acceptance Model (TAM), where Davis

(1989b) emphasized that behavioral intention is one of the strongest predictors of actual behavior, particularly in technology usage. The high β value in this study further supports the idea that a user's intent plays a critical role in determining whether they will ultimately adopt and utilize a system, bridging the gap between intention and action.

In educational contexts, this relationship is significant as it highlights the direct impact of users' intentions on their engagement with educational technologies. When students or educators intend to use digital learning tools or AI-based systems, they are more likely to integrate these technologies into their daily educational routines. Recent research, such as Abbad (2021), supported it, which found that students' behavioral intention towards e-learning platforms strongly predicted their actual usage of these tools. Similarly, Panergayo (2021) observed that behavioral intention played a significant role in using learning management systems (LMS), particularly in online learning environments. These findings underscore the critical role of behavioral intention as a key driver in turning potential users into active users of educational technology.

Moreover, recent studies have further elaborated on how fostering strong behavioral intentions can facilitate actual technology adoption. For instance, Jameel et al. (2022), explored technology use in remote learning during the COVID-19 pandemic and demonstrated that behavioral intention was a decisive factor in whether students engaged with online platforms. Another study by Strzelecki (n.d.) examined how behavioral intention towards AI-driven tools in educational settings translated into frequent and meaningful usage by teachers. These findings highlight the importance of creating positive perceptions and attitudes around the technology to strengthen users' intentions. Fostering strong behavioral intentions through effective communication, training, and showcasing the technology's usefulness can significantly enhance the likelihood of consistent and meaningful use of educational technologies.

Lastly, the hypothesis testing demonstrates the critical factors influencing technology acceptance in educational contexts. Perceived Usefulness and Perceived Ease of Use significantly affect users' Attitude Toward Using, which, in turn, strongly drives Behavioral Intention. Finally, Behavioral Intention is a powerful predictor of Actual Usage, confirming the validity of the Technology Acceptance Model (TAM) in this research context. These findings emphasize the importance of focusing on the perceived benefits and ease of use of educational technologies to foster positive attitudes and drive actual usage among educators and students.

Conclusion

This research explored the key factors shaping the adoption of artificial intelligence (AI) in Islamic studies education, employing the Technology Acceptance Model (TAM) as the guiding framework. The findings revealed that Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) significantly influence Attitude Toward Using (ATU) AI-based technologies, with PEOU having a more substantial effect, emphasizing the importance of user-friendly AI tools in enhancing acceptance. Additionally, ATU emerged as a robust predictor of behavioral intention (BI) to adopt AI, leading to actual usage and indicating that positive attitudes are crucial for successful technology integration. Based on these insights, recommendations include prioritizing intuitive AI applications, providing clear instructions and support, highlighting practical benefits, and offering continuous training for educators

and students to build confidence. Moreover, institutions should develop supportive policies for AI integration within the curriculum. Future research could delve into cultural and ethical dimensions, assess the impact on academic performance, and conduct longitudinal studies to evaluate the long-term sustainability of AI adoption in Islamic education.

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