Impact of Student Attitudes toward AI Educational Technology and Use Perceptions: Evidence from Islamic Studies Using the Technology Acceptance Model

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Abstract

Objectives: This study aimed to investigate the influence of perceived usefulness and perceived ease of use on student attitudes towards AI-powered educational technology in Islamic studies.

Methods: The study employed the Technology Acceptance Model (TAM) as its theoretical framework. A sample of 365 students from the College of Sharia and Fundamentals of Religion at the Islamic University in Medina participated in the survey.

Findings: The results demonstrated that both perceived usefulness and perceived ease of use significantly influenced not only students' overall attitudes towards AI educational technology but also the individual components of those attitudes: cognitive (beliefs), affective (emotions), and behavioral (adoption and engagement). Furthermore, the study supported the Theory of Planned Behavior, revealing that affective and cognitive components partially explained the behavioral component. Students' behavioral attitude towards AI technology was significantly explained by perceived usefulness, perceived ease of use, student affective attitude, and student cognitive attitude. The model exhibited strong explanatory power across all domains (affective, cognitive, and behavioral) with adjusted R-squared values of 28.4%, 39%, and 26%, respectively.

Novelty: This study contributes to the understanding of student adoption of AI educational technology in Islamic studies by demonstrating the impact of perceived usefulness and ease of use on all dimensions of student attitudes, encompassing beliefs, emotions, and most importantly, behavior (adoption and engagement).

Keywords: Perceived Usefulness(PU); Perceived Ease of Use(PEU) behavioral attitude AI technology

1. Introduction

The adoption and application of modern AI communication and information technology in Islamic studies in higher education define an area that is intensely interrupting the interests of scholars across a wide variety of disciplines including education, information technology, philosophy, sociology, psychology, and behavioral science [1,2]. This study revealed a scale to measure high school students' feelings about AI interviews for college admissions. It also showed students' attitudes can be influenced by information about AI[3]The vast potential such technology entails for Islamic studies in higher education covers critical aspects such as allowing students to reliably gain access to the wealth of digital and computer-based learning resources, simplifying the process of self and independent learning, and accommodating effective collaboration and communication with peers and faculty [4,5]. In particular, modern AI communication and information technology including typically provide students majoring in Islamic studies with extraordinary digital approaches to the study of major subjects including Qur'an science, Hadith science, Islamic history, Aqidah (or theology), Islamic philosophy, Islamic law (or Fiqh), Islamic legal theory, biography of the prophet, Islamic architecture, and Islamic literature [6,7] .Along these lines, one may argue that modern information and communication technology manifested in the tools and capabilities it provides to students of Islamic studies may be largely responsible for turning Islamic higher education into a more dynamic field of human inquiry [8].In this fashion, Islamic higher education can be made more interactive, engaging, and accessible for current learners while attracting the interests of potential learners and future scholars [9].For instance, modern AI information and communication technology may provide students of Islamic studies with the capabilities necessary to gain access to a vast amount of online learning resources and materials, which translates to marginal expansion of knowledge boundaries, proficient exploitation of search functions, and enlightened exploration of novice subjects of inquiry [10].This includes digital Islamic law libraries, theology databases, and websites that offer Islamic history books, Islamic philosophy articles, Qur'an translations, Hadith collections, and other scholarly works and fields of knowledge in Islamic studies [11].

In view of the foregoing, though the potential benefits AI technologies may entail for higher education Islamic studies are overwhelming, such benefits essentially hinge on the extent to which academic institutions accept and utilize the technologies in the first place [12]. For instance, the benefits of AI educational interventions are hardly achievable in case instructors or students fail short of accepting or adopting such interventions. Toward this end, this study evaluates the impact of perceived usefulness (PU) and perceived ease of use (hereafter, PEU) on student attitudes toward AI educational technology. The study employs a sample of 365 students of Islamic studies at the college of sharia and fundamentals of religion at the Islamic university in Medina. The study adopts the technology acceptance model (TAM) as its theoretical framework where PU and PEU are hypothesized to drive student attitude toward AI educational technology [13,14]. The study further distinguishes among the three student attitude components, and tests the theory of planned behavior claim (TPB) that affective and cognitive components tend to partially explain the behavioral component. In this fashion the study advances the following research questions:

RQ1: What is the impact of perceived usefulness on student attitude toward AI educational technology?

RQ2: What is the impact of perceived ease of use on student attitude toward AI educational technology?

RQ3: What is the impact of perceived usefulness on the components of student attitude toward AI educational technology?

RQ4: What is the impact of perceived ease of use on the components of student attitude toward AI educational technology?

RQ5: What is the impact of the affective component of student attitude toward AI educational technology on the behavioral component?

RQ6: What is the impact of the cognitive component of student attitude toward AI educational technology on the behavioral component?

The rest of the study is organized in terms of literature review, research design, data analysis & empirical results, and concluding remaks.

Literature Review

The researcher [14] formulates TAM in terms of the two constructs of PU and PEU. The researcher modifies the initial TAM to allow for the characteristics of the technological intervention to have a behavioral impact on the perceptions of users. The researchers [16] explain individual-level performance in terms of respective PU and PEU levels of technology acceptance The study [17] investigates factors influencing higher education teachers' continued use of technology in emerging economies. The findings show that perceived usefulness, ease of use, self-efficacy, and facilitating conditions significantly influence teachers' continuous use intention.) The author empirically tests an extended TAM and summarize that the levels of student utilization and acceptance of educational Wikis are driven by PU and PEU. The study by [18] enlist PU and PEU among the individual factors affecting student intention to use AI learning systems. However, it doesn't consider their actual usage over time. A gap exists in understanding the gap between intention and behavior - why some students might not use the platform even if they initially have positive aims. The study [18] underscore the role PU and PEU may assume as latent variables when modeling the acceptance of Moodle among students. Another study [19] explores the] acceptance of mobile technologies and mobile learning in higher education. They use a survey to assess factors influencing students' willingness to use mobile devices for learning. A gap exists in understanding how students actually integrate M-learning into their studies and what factors influence sustained use over time. Moreover, the study focuses on student perceptions, but a gap remains in exploring faculty perspectives on M-learning implementation and its effectiveness in their courses.

The researchers [20] supply an evidence from vocational education that instructors' decision to utilize AI educational technology depends on the underlying level of digital competence moderated by PU and PEU.The Authors [2] employ the variables of student self-efficacy and prior experience as antecedents of PU and PEU to the context of e-learning in higher education in Saudi Arabia. The authors [13] model PU & PEU in terms of student motivation and continuous learning intention. The research. [21] categorize exogenous as well as dependent TAM variables into individual, contextual, and behavioral and document that PU and PEU jointly drive behavioral intention and use behavior in higher education. The study [22] report that student-level PU and PEU have a strong impact on the effective integration of e-learning tools. The research [23]) incorporate PU and PEU among the personal factors the acceptance and adoption of mobile learning in higher education. Cheng (2015) contends that PU and PEU strongly contribute to the compatibility affecting the adoption and acceptance of mobile learning in higher education. The research [24] contend that PU and PEU tend to significantly stimulate student behavioral intention to use learning management systems in higher education. The use PU and PEU to predict instructors' behavioral intention to adopt learning management systems. The study shows that PU and PEU are replicated positively into the extent to which combined learning is accepted in executive higher education. . The PU and PEU could contribute to student satisfaction with blended learning in higher education. The researchers. adhere to and extended version of TAM and describe that PU and PEU student acceptance of and intention to use AI educational technology. The author examines factors influencing educators' use of ChatGPT in Jordanian universities. They use the Technology Acceptance Model to assess how PU and PEU affect educators' willingness to adopt ChatGPT in their teaching. [25]. However, the study doesn't explore how educators integrate ChatGPT into their teaching practices or address potential challenges like student misuse or limitations of the technology itself. There are various barriers to integrating a new technology into existing courses, such as workload concerns, lack of training, or difficulty adapting teaching styles.

. The research by authors [23,26] include PU and PEU among the set of variables explaining student use of e-learning platforms in higher education. The study describes PU and PEU as essential factors when academic institutions adopt mobile learning in higher education The model [27] instructors' PU and PEU as a function of cultural values. focusing on how cultural dimensions like individualism-collectivism and uncertainty avoidance impact teachers' perceptions and ultimately their willingness to use technology for teaching. The study doesn't explore how cultural factors might influence teachers' needs for training or support when adopting new technologies.

In the light of the preceding review, PU and PEU of higher education students of Islamic studies were hardly measured or investigated [6] Toward this end, the study complements the extant literature with TAM evidence of students of Islamic studies at the college of sharia and fundamentals of religion at the Islamic university in Medina. The study specifies student attitude, along with its affective, cognitive, and behavioral components, toward AI educational interventions in terms of PU and PEU. Whereas the affective component addresses feelings, the cognitive component represents thoughts and beliefs, and the behavioral component sums up the rather observable behavioral reactions [28]. In this regard, the study further test the TPB claim that the behavioral component is partially explained by affective and cognitive components [29].

The reviewed literature highlights a various factors influencing technology adoption in education. PU , PEU and self-efficacy emerge as consistent themes. However, a critical gap remains in understanding the translation of intention into constant use behavior.

The research discourses this gap in knowledge by aiming on Islamic studies students and AI educational technology. Existing research often focuses exclusively on the overall attitude towards technology. This study goes beyond that and distinctively combines the Technology Acceptance Model and the Theory of Planned Behavior, providing a more comprehensive understanding of student behavior towards AI technology.

2. Methodology

To answer the research questions above, the study adopts the quantitative research paradigm to quantify the extent to which student attitude toward AI educational technology can be explained by the TAM variables of PU and PEU. The study thus maintains classic quantitative ontological, epistemological, and axiological assumptions. Ontologically, the study assumes that the variables of student attitude toward AI educational technology, student PU, and student PEU are observable and objectively measurable. Epistemologically, the study assumes that the individual effects of PU and PEU on student attitude toward AI educational technology can be objectively quantified and tested. Axiologically, the study maintains that observing and documenting the relationship between student use perceptions (i.e., PU and PEU) and student attitude toward AI educational technology will inform theory and practice with respect to the adoption and utilization of modern technology in higher education Islamic studies.

Study Sample

The study employs a sample size of 365 students at the college of sharia and religious fundamentals at the Islamic University in Medina..The study applies Cochran's (1977) sample size determination framework to a total student population of 7163 at a 95% confidence interval, 5% margin of error, and 50% population proportion as follows: 365 = [(1.96^2) *0.5*(1-0.5) *(0.05^-2)] / [1 + {(1.96^2) *0.5*(1-0.5) *(0.05^-2) *(7163^-1)}].

Variables' Measurement and coding

Student attitude toward AI educational technology along with the three components is measured according to Suh's & Ahn (2022) validated scale measurement of student attitude toward AI (Table 1). PU and PEU are both measured according to the original measurement scale reported in [15] Table 2 & Table 3). All items to variable measurements are captured on a five-point Likert-type scale. All variables are measured based on average item score and are coded as 1 for lowest score, 2 for lower score, 3 for average score, 4 for high score, and 5 for highest score.

Cognitive component	Affective component	Behavioral component
I think that it is important to learn about AI.	AI is very important for developing society.	I want to work in the field of AI.
AI class is important.	I think AI makes people's lives more convenient.	I will choose a job in the field of AI.
I think that lessons about AI should be taught.	AI is related to my life.	I would participate in a club related to AI if there was one.
I think every student should learn about AI	I will use AI to solve problems in daily life.	I like using objects related to AI.
	AI helps me solve problems in real life.	It is fun to learn about AI.
	I will need AI in my life in the future.	I want to continue learning about AI.
	AI is necessary for everyone.	I'm interested in AI-related TV programs or online videos.
	AI produces more good than bad.	I want to make something that makes human life more convenient through AI.
	AI is worth studying.	I am interested in the development of AI.
	I think that most jobs in the future will require knowledge related to AI.	It is interesting to use AI.
		I think that there should be more class time devoted to AI in school.
		I think I can handle AI well.

Table 1: Measurement of Student Attitude Toward AI Educational Technology

Using the system in my job would enable me to accomplish tasks more quickly
Using the system would improve my job performance
Using the system in my job would increase my productivity
Using the system would enhance my effectiveness
Using the system would make it easier
I would find the system useful

Table 2: Measurement of PU

Learning to operate the system would be easy for me
I would find it easy to get the system to do what I want it to do
My interaction with the system would be clear and understandable
I would find the system to be flexible to interact with
It would be easy for me to become skillful at using the system
I would find the system easy to use

Table 3: Measurement of PEU

3. Results & Discussion

To answer RQ1 and RQ2, the study estimates a linear model to explain student attitude toward AI educational technology in terms of the TAM variables of PU and PEU. The model estimation is carried out according the functional form:

FF (1): student attitude toward AI educational technology = f (PU; PEU)

The model is specified as follows while assuming that the underlying data generating process satisfies the Gauss-Markov properties of correct specification and identically and independently distributed error terms with zero mean and constant variance:

*SF (1): student attitude toward AI educational technology (i) = b0 + b1*PU (i) + b2*PEU (i) + e (i)*

Where (i) is an index for the student included in the dataset and takes discrete values between 1 and 365; b0 is an intercept parameter estimate; b1 and b2 are coefficients or parameter estimates; and e is a Gauss-Markov error term with an average value of zero and constant variance everywhere across the study sample.

The statistical model output shows that the model has a significant explanatory power of 47.7 % as measured by adjusted R squared (see Table 4). The statistical output also shows that both TAM variables of PU and PEU were replicated positively in student attitude toward AI educational technology. Furthermore, the individual impacts of the two independent variables were well-pronounced and statistically significant at the 5% type-I error.

SUMMARY OUTPUT								
Regression Statistics								
Multiple R	0.692764317							
R Square	0.479922399							
Adjusted R Square	0.477049042							
Standard Error	0.649326659							
Observations	365							
ANOVA								
	df	*SS*	*MS*	*F*	*Significance F*			
Regression	2	140.8438563	70.42192817	167.024986	4.05822E-52			

Residual	362	152.6282898	0.42162511					
Total	364	293.4721461						
[redacted]								
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
ease	1.363422945	0.12887914	10.57908166	5.7024E-23	1.109977114	1.61686878	1.10997711	1.616868775
Perceived Usefulness	0.377582682	0.039128862	9.649723006	9.2953E-20	0.300634255	0.45453111	0.30063426	0.454531108
Perceived Ease of Use	0.268464781	0.035085745	7.651676803	1.8153E-13	0.199467302	0.33746226	0.1994673	0.337462261

Table 4: Answering RQ1 & RQ2. (Regressing student attitude toward AI technology on PU & PEU)

To answer RQ3 and RQ4, the study estimates three linear models to explain: [1] affective student attitude toward AI educational technology in terms of the TAM variables of PU and PEU, [2] cognitive student attitude toward AI educational technology in terms of the TAM variables of PU and PEU, and [3] behavioral student attitude toward AI educational technology in terms of the TAM variables of PU and PEU. The three model estimations are carried out according the functional forms:

FF (2): affective student attitude toward AI educational technology = f (PU; PEU)

FF (3): cognitive student attitude toward AI educational technology = f (PU; PEU)

FF (4): behavioral student attitude toward AI educational technology = f (PU; PEU)

The three models are specified as follows while assuming that the underlying data generating process satisfies the Gauss-Markov properties of correct specification and identically and independently distributed error terms with zero mean and constant variance:

*SF (2): affective student attitude toward AI educational technology (i) = b0 + b1*PU (i) + b2*PEU (i) + e (i)*

*SF (3): cognitive student attitude toward AI educational technology (i) = b0 + b1*PU (i) + b2*PEU (i) + e (i)*

*SF (4): behavioral student attitude toward AI educational technology (i) = b0 + b1*PU (i) + b2*PEU (i) + e (i)*

Where (i) is an index for the student included in the dataset and takes discrete values between 1 and 365; b0 is an intercept parameter estimate; b1 and b2 are coefficients or parameter estimates; and e is a Gauss-Markov error term with an average value of zero and constant variance everywhere across the study sample.

The statistical models output shows that the model have significant explanatory powers of 28.4% (affective), 39% (cognitive), and 26% (behavioral) respectively as measured by adjusted R squared (see Table 5 for the affective attitude component, Table 6 for the cognitive attitude component, and Table 7 for the behavioral attitude component). The statistical output also shows that both TAM variables of PU and PEU were replicated positively in the three components to student attitude toward AI educational technology. Furthermore, the individual impacts of the two independent variables were well-pronounced and statistically significant at the 5% type-I error for every individual attitude component.

SUMMARY OUTPUT								
Regression Statistics								
Multiple R	0.53683381							
R Square	0.288190539							
Adjusted R Square	0.28425789							
Standard Error	0.990104554							
Observations	365							
ANOVA								
	df	*SS*	*MS*	*F*	*Significance F*			
Regression	2	143.6768012	71.838401	73.28153	1.896E-27			
Residual	362	354.871144	0.980307					
Total	364	498.5479452						
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	1.376702366	0.196517148	7.0055076	1.21E-11	0.99024377	1.763160965	0.990243766	1.763160965
Perceived Usefulness	0.421086913	0.059664368	7.0575945	8.69E-12	0.30375462	0.538419209	0.303754618	0.538419209
Perceived Ease of Use	0.231666948	0.053499353	4.3302757	1.93E-05	0.12645839	0.336875502	0.126458395	0.336875502

Table 5: Regressing affective student attitude toward AI educational on PU & PEU

In Table 5, the results of the regression analysis show that there is a statistically significant relationship between perceived usefulness (PU) and perceived ease of use (PEU) and affective student attitude toward AI educational tools. The multiple R value of 0.537 indicates that the model explains 28.8% of the variance in affective student attitude. The ANOVA table shows that the F-statistic is significant, which indicates that the model is a good fit for the data. The analysis also shows that both PU and PEU have positive relationships with affective student attitude, with PU having a slightly stronger effect. These results suggest that students who find AI educational tools to be both useful and easy to use are more likely to have positive attitudes toward them.

SUMMARY OUTPUT								
Regression Statistics								
Multiple R	0.627537932							
R Square	0.393803856							
Adjusted R Square	0.390454706							
Standard Error	0.883541491							
Observations	365							
ANOVA								
	df	*SS*	*MS*	*F*	*Significance F*			
Regression	2	183.5816474	91.79082371	117.5832255	4.49763E-40			
Residual	362	282.5936951	0.780645566					
Total	364	466.1753425						
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	1.001671813	0.175366383	5.71188045	2.33326E-08	0.656807015	1.346536611	0.656807015	1.34653661
Perceived Usfulness	0.426497703	0.053242806	8.010428754	1.58212E-14	0.321793659	0.531201747	0.321793659	0.53120175
Perceived Ease of Use	0.310879707	0.047741319	6.511753559	2.48432E-10	0.216994549	0.404764865	0.216994549	0.40476486

Table 6: Regressing cognitive student attitude toward AI educational technology on PU & PEU

The coefficient for PU is 0.4265, which is positive and significant ($p < 0.001$). This indicates that a one-unit increase in PU is associated with a 0.4265-unit increase in cognitive student attitude, holding PEU constant.

Both perceived usefulness and perceived ease of use have significant positive relationships with cognitive student attitude toward AI educational technology. Perceived usefulness has a slightly stronger effect than perceived ease of use on cognitive attitude. The model explains a moderate amount of variance in cognitive student attitude (39%).

SUMMARY OUTPUT								
Regression Statistics								
Multiple R	0.513335375							
R Square	0.263513208							
Adjusted R Square	0.25944422							
Standard Error	0.889087245							
Observations	365							
ANOVA								
	df	*SS*	*MS*	*F*	*Significance F*			
Regression	2	102.3846275	51.19231375	64.76136579	9.05437E-25			
Residual	362	286.1523588	0.790476129					
Total	364	388.5369863						
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	1.711894655	0.176467111	9.700927549	6.24499E-20	1.364865233	2.058924078	1.36486523	2.05892408
Perceived Usufulness	0.285163428	0.053576997	5.322497447	1.79913E-07	0.179802185	0.390524672	0.17980218	0.39052467
Perceived Ease of Use	0.262847688	0.048040979	5.471322484	8.35295E-08	0.168373239	0.357322138	0.16837324	0.35732214

Table 7: Regressing cognitive student attitude toward AI educational technology on PU & PEU

The Key findings in table 7 explains a moderate 26% of the variance in cognitive student attitude. Both PU and PEU have significant positive relationships with cognitive student attitude. The PU has a slightly stronger effect on cognitive attitude compared to PEU. Overall students who perceive

AI educational technology as more useful and easier to use tend to have more positive cognitive attitudes towards it. Compared to Table 6, this model explains a slightly lower percentage of variance (26. % vs. 39 %) in cognitive student attitude. However, the positive relationships between PU and PEU with cognitive attitude remain significant and similar in effect size.

To answer RQ5 and RQ6, the study estimates a linear model to explain behavioral student attitude toward AI educational technology in terms of the TAM variables of PU and PEU in conjunction with the two other attitude components of affective attitude and cognitive attitude. The model estimation is carried out according the functional form:

FF (5): behavioral student attitude toward AI educational technology = f (PU; PEU)

The model is specified as follows while assuming that the underlying data generating process satisfies the Gauss-Markov properties of correct specification and identically and independently distributed error terms with zero mean and constant variance:

*SF (5): behavioral student attitude toward AI educational technology (i) = b0 + b1*PU (i) + b2*PEU (i) + b3*affective attitude (i) + b4*cognitive attitude (i) + e (i)*

Where (i) is an index for the student included in the dataset and takes discrete values between 1 and 365; b0 is an intercept parameter estimate; b1, b2, b3, and b4 are coefficients or parameter estimates; and e is a Gauss-Markov error term with an average value of zero and constant variance everywhere across the study sample.

The statistical model output shows that the model has a significant explanatory power of almost 33 % as measured by adjusted R squared (see Table 8). The statistical output also shows that both TAM variables of PU and PEU along with affective attitude and cognitive attitude were replicated positively in behavioral student attitude toward AI educational technology. Furthermore, the individual impacts of the four independent variables were well-pronounced and statistically significant at the 5% type-I error.

SUMMARY OUTPUT								
Regression Statistics								
Multiple R	0.580667249							
R Square	0.337174454							
Adjusted R Square	0.329809725							
Standard Error	0.845793907							
Observations	365							
ANOVA								
	df	*SS*	*MS*	*F*	*Significance F*			

Regression	4	131.004746	32.75118653	45.782334	4.39E-31			
Residual	360	257.53224	0.715367334					
Total	364	388.536986						
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	1.25798066	0.1826034	6.889141487	2.517E-11	0.898877	1.61708403	0.89887729	1.61708403
Perceived Usefulness	0.218268477	0.0462512	4.719195931	3.395E-06	0.127312	0.30922495	0.127312	0.30922495
Perceived Ease of Use	0.1531672	0.05182951	2.955212077	0.0033303	0.051241	0.25509385	0.05124055	0.25509385
Cognitive Attitude	0.12792797	0.05708727	2.240919441	0.0256404	0.015662	0.24019439	0.01566155	0.24019439
Affective Attitude	0.164665522	0.04878694	3.37519684	0.000818	0.068722	0.26060872	0.06872233	0.26060872

Table 8: Answering RQ5 and RQ6. (Regressing behavioral attitude on PU, PEU, affective attitude, and cognitive attide)

The Key findings in above model (Table 8) explains a moderate correlation 33.7% of the variance in behavioral student attitude.

Significant positive impacts: All four predictors have significant positive relationships with behavioral attitude:

- PU: A one-unit increase in PU is associated with a 0.218-unit increase in behavioral attitude.
- PEU: A one-unit increase in PEU is associated with a 0.153-unit increase in behavioral attitude.
- Cognitive attitude: A one-unit increase in cognitive attitude is associated with a 0.128-unit increase in behavioral attitude.
- Affective attitude: A one-unit increase in affective attitude is associated with a 0.165-unit increase in behavioral attitude.

Among the predictors, affective attitude has the strongest effect on behavioral attitude.

Impact of affective attitude on behavioral attitude (RQ5): Affective attitude has a significant positive impact on behavioral attitude, suggesting that positive emotions and feelings towards AI educational technology are associated with more favorable behavioral tendencies towards using it. **Impact of cognitive attitude on behavioral attitude(RQ6):** The Cognitive attitude also has a significant positive impact on behavioral attitude, indicating that favorable beliefs and thoughts about AI educational technology contribute to more positive behavioral intentions.

Innovations and Comparison: This study introduces novel insights by examining the effects of PU and PEU on various components of student attitudes (affective, cognitive, and behavioral). Compared to previous research [26,][27] which primarily focused on general technology adoption, our findings provide a deeper comparison by segmenting attitudes into distinct components. This segmentation enhances the understanding of how different aspects of attitudes toward AI educational technology interact with PU and PEU. This approach provides a more nuanced understanding of how PU and PEU influence different aspects of attitudes

4. Conclusion

The study reports that the student behavioral attitude toward AI educational technology is significantly explained in terms of perceived usefulness, perceived ease of use, student affective attitude toward, and student cognitive attitude. By demonstrating the role of PU, PEU, cognitive and affective attitudes on behavioral intentions, it offers evidence for the potential of AI in this field. Explicitly, a one-unit increase in PU is associated with a 0.218-unit increase in behavioral attitude, while a similar increase in PEU leads to a 0.153-unit rise. Our findings provide robust evidence that perceived usefulness, perceived ease of use, cognitive and affective attitudes all demonstrably influence student behavioral intentions towards AI technology. This confirms the relevance of the Theory of planned behavior in this context, and underscores the importance of fostering positive perceptions and attitudes to drive technology adoption and utilization. The study confirms the strong positive impact of AI on student attitude and behavior, suggesting its promising role in enhancing learning experiences in Islamic studies. The perceived usefulness and ease of use alone are not enough. Cultivating positive cognitive and affective attitudes, encompassing both beliefs and emotions, is crucial for sustained technology adoption and engagement. Building responsible AI frameworks encompassing data privacy, fairness, and algorithmic bias mitigation is paramount for ensuring ethical and equitable educational experiences for all. The recommendations for improvement and limitations identified can guide future research to further optimize the integration and utilization of AI for improving learning experiences in Islamic studies and beyond.

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