

The 6th Advances in Business Research International Conference 2024

DoubleTree Resort by Hilton Penang, Batu Ferringhi, Penang, Malaysia, 30 May 2024

Organised by: Faculty of Business and Management, UiTM Puncak Alam, Selangor, Malaysia

Validating the Acceptance of Artificial Intelligence (AI) in Higher Education Institutions using the Technology Acceptance Model (TAM)

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Abstract

The incorporation of artificial intelligence (AI) into the education system in Malaysia remains unclear. This research will adopt the Technology Acceptance Model (TAM) to assess users' perceived usefulness, ease of use, and intention to accept AI-powered learning applications. An online survey questionnaire was randomly distributed to students and staff of higher education institutions in Malaysia. Three hundred eighty-three responses were collected for data analysis. The findings revealed that perceived usefulness and perceived ease of use positively influence the intention to use AI in higher education institutions. Furthermore, the intention to use AI influences the acceptability of AI in higher education institutions.

Keywords: Artificial intelligence, Perceived Usefulness, Perceived Ease-of-Use, Intention.

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DOI: <https://doi.org/10.21834/e-bpj.v10iSI26.6810>

1.0 Introduction

Integrating Artificial Intelligence (AI) in higher education has become increasingly prevalent, offering innovative teaching, learning, and administrative solutions. These technologies, from AI-powered tutoring systems to adaptive learning platforms and automated grading systems, promise to enhance educational outcomes, improve efficiency, and provide personalized learning experiences. Despite the growing interest in AI adoption in higher education Institutions (HEIs), many institutions face significant challenges, such as insufficient digital infrastructure and a lack of AI-related knowledge and training among lecturers, which ultimately affect their acceptance of AI-based systems (Aziz et al., 2023). In addition, the success of AI adoption in HEIs largely depends on the acceptance of these technologies by key stakeholders, including students, faculty, and administrators. The Technology Acceptance Model (TAM), initially developed by Davis (1989), has been widely used to understand and predict technology acceptance in various domains. TAM posits that two primary factors, Perceived Usefulness (PU) and Perceived Ease of Use (PEOU), significantly influence an individual's intention to use a technology, which in turn predicts actual usage. Given its robust theoretical foundation, TAM has been validated and extended

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across multiple contexts, including education. However, the rapid advancement of AI technologies and their unique characteristics necessitate re-examining and validating TAM within the specific context of AI adoption in higher education.

In recent years, a growing body of research has focused on understanding the factors influencing AI acceptance in educational settings, with TAM as a foundational framework. For instance, Wang et al. (2024) examine the influence of AI literacy and subjective norms on students' attitudes toward generative AI technology and perceived behavioral control and attitude are mediated by the impact of AI literacy and subjective norms on generative AI usage intention. Similarly, Zhang et al. (2021) examined the role of PU and PEOU in students' acceptance of AI-based learning platforms, highlighting the importance of these factors in shaping positive attitudes toward AI adoption. Despite these advances, there remain gaps in understanding how TAM applies to the diverse and evolving landscape of AI technologies in higher education. This study aims to validate the Technology Acceptance Model in the context of AI adoption in higher education institutions, incorporating the latest empirical findings from 2020 to 2024. The specific objectives of the current study were to examine the relationship between PU and PEOU and the intention to accept AI among HEI students. By examining the roles of PU and PEOU and their intention to use, this research provides a comprehensive understanding of the factors influencing AI acceptance among key stakeholders in higher education. The findings of this study will not only contribute to the theoretical advancement of TAM in the context of AI but also offer practical insights for HEIs seeking to foster successful AI adoption and integration.

2.0 Literature Review

The current study employed the Technology Acceptance Model (TAM) as the foundation of the research framework development. By focusing on perceived usefulness, perceived ease of use, and intention, TAM can help predict and explain user acceptance of AI technologies. This understanding is crucial for higher education institutions. The following subsections will further discuss each of the current study's variables.

2.1 Acceptance of Artificial Intelligence (AI)

Artificial Intelligence (AI) device development and use have gained traction recently (Gursoy et al., 2019). AI will significantly impact society during the next few decades (Schepman, 2022), and it is expected to be one of the most valuable technologies in the coming years (Chai et al., 2020). People use and continue to develop new technology to help them in their daily lives and make them more comfortable (Razia et al., 2023). AI is an example of a technology that is receiving much interest in the media, academia, and politics worldwide (Choi, 2021). AI is a fast-evolving field with enormous potential for expanding and improving teaching and learning in higher education (Razia et al., 2023).

Artificial intelligence in education has been integrated into administration, instruction or teaching, and learning (Chen et al., 2020). AI uses enhanced capabilities of programs and software, such as algorithmic machine learning, which allows computers to execute activities that require human-like intelligence and adapt to the present environment (Chen et al., 2020). Using AI technology in higher education institutions is considerably simpler for new students and academics than for older generations of these two groups (Razia et al., 2023). Artificial Intelligence technology literacy among students and faculty is predicted to be greater than ever (Razia et al., 2023). As a result of the preceding research, the present study will concentrate on perceived usefulness, perceived ease-of-use, and intention to use as variables influencing the acceptance of Artificial Intelligence (AI) in higher education in Malaysia.

2.2 Perceived Usefulness (PU)

Perceived usefulness is a person's degree of conviction that technology would improve their performance and relieve them of work (Ayanwale et al., 2022). Perceived usefulness predicts behavioral intention and, hence, the result of AI use (Darmansyah, Hendratmi, & Aziz, 2020). Since the introduction of AI in education nearly three decades ago, AI has been viewed as a powerful tool for facilitating new paradigms for instructional design, technological development, and education research that would otherwise be impossible to develop in traditional educational modes (Hwang et al., 2020). The rise of AI technologies has spurred research into how PU affects AI adoption. Burton et al. (2020) found that PU in AI is closely related to the technology's ability to perform tasks better than humans, enhance decision-making, and reduce workload. Several recent studies have emphasized the importance of PU in determining educators' and students' acceptance of AI-driven tools. Cheng et al. (2022) examined the acceptance of AI-powered personalized learning systems among university students. The findings indicated that students who believed that AI could provide tailored learning experiences and improve academic performance had a higher intention to use these systems. This highlights the critical role of PU in shaping students' attitudes towards AI in education.

In addition, according to a study by Sun et al. (2023), educators' acceptance of AI-based automated grading systems was primarily driven by their perception of the system's usefulness in saving time and reducing grading errors. The study concluded that when educators recognize the practical benefits of AI in assessments, their likelihood of adopting such tools increases. This study underscores the importance of highlighting the practical benefits of AI technologies to foster positive intentions among educators. In this study, we will observe the influence of perceived usefulness on the acceptance of AI in higher education.

H1: Perceived usefulness influences the intention to use AI in higher education.

2.3 Perceived Ease of Use (PEOU)

Perceived ease of use is the degree to which a person feels that utilizing a particular system will need only a few steps (Kashive et al., 2020). Recent studies emphasize the significant role of PEOU in AI acceptance among educators and students. For instance, Zhang et

al. (2021) conducted a study on the adoption of AI-based learning platforms among university students, finding that PEOU significantly predicted students' intention to use these platforms. The research indicated that when students perceive AI technologies as easy to use, they are more likely to develop a positive intention to engage with these tools, increasing the likelihood of actual adoption. Similarly, Nguyen and Pham (2022) explored the acceptance of AI-driven language learning applications among university students. The findings indicated that PEOU significantly influenced students' willingness to engage with these applications, particularly in intuitive design and user-friendly interfaces. This underscores the importance of designing AI tools that are accessible and easy to use in educational contexts.

Their perception of ease of use heavily influences educators' adoption of AI technologies. In a study by Li and Zhao (2023), PEOU was identified as a key factor in the acceptance of AI-based instructional tools among secondary school teachers. The research revealed that teachers who found AI tools easy to integrate into their existing teaching practices were more likely to adopt them. Moreover, Wang et al. (2024) investigated the role of PEOU in the adoption of AI-driven grading systems in K-12 education. The findings suggested that teachers' perceptions of the ease of use of these systems, particularly in automating routine tasks and providing clear instructions, were crucial in their decision to use AI for grading. Based on the previous studies discussed above consistently show that when AI systems are perceived as easy to use, their adoption rates increase among both educators and students. Thus, the current study hypothesized as follows:

H2: Perceived ease of use positively influences the intention to use AI in higher education.

2.4 Intention to Use

Intention to use, a key concept derived from the Technology Acceptance Model (TAM), refers to the likelihood that an individual will engage with a particular technology. It has been widely studied as a predictor of actual technology adoption. In education, where artificial intelligence (AI) is increasingly being integrated into teaching and learning processes, understanding how intention to use influences AI acceptance is critical. Recent studies consistently demonstrate that intention to use strongly predicts AI adoption among educators and students. For instance, Yang and Wang (2021) explored the adoption of AI-based tutoring systems in secondary education. They found that students' intention to use these systems significantly predicted actual usage. The study highlighted that when students have a firm intention to engage with AI tools, they are more likely to integrate them into their learning routines, leading to higher adoption rates.

Similarly, Liu et al. (2022) examined the role of intention to use in the adoption of AI-driven educational platforms among university faculty. The findings revealed that faculty members with a higher intention to use AI platforms were more likely to adopt these technologies in their teaching practices. This underscores the importance of fostering a positive intention to use AI among educators to enhance technology acceptance. Several studies have investigated the factors that influence intention to use AI in educational settings. For example, Chen and Xu (2023) identified perceived usefulness and perceived ease of use as key determinants of intention to use AI technologies among teachers. Their study found that when teachers perceive AI tools as helpful and easy to use, their intention to adopt these tools increases, leading to higher acceptance rates. This suggests that the intention to use is a critical determinant of AI acceptance in education, consistently predicting educators' and students' adoption of AI technologies. Thus, the following hypothesis is designed:

H3: The intention to use AI influences AI acceptance in higher education.

To sum up, based on the presented discussion above, the current study develops a research model as illustrated in Fig. 1 below:

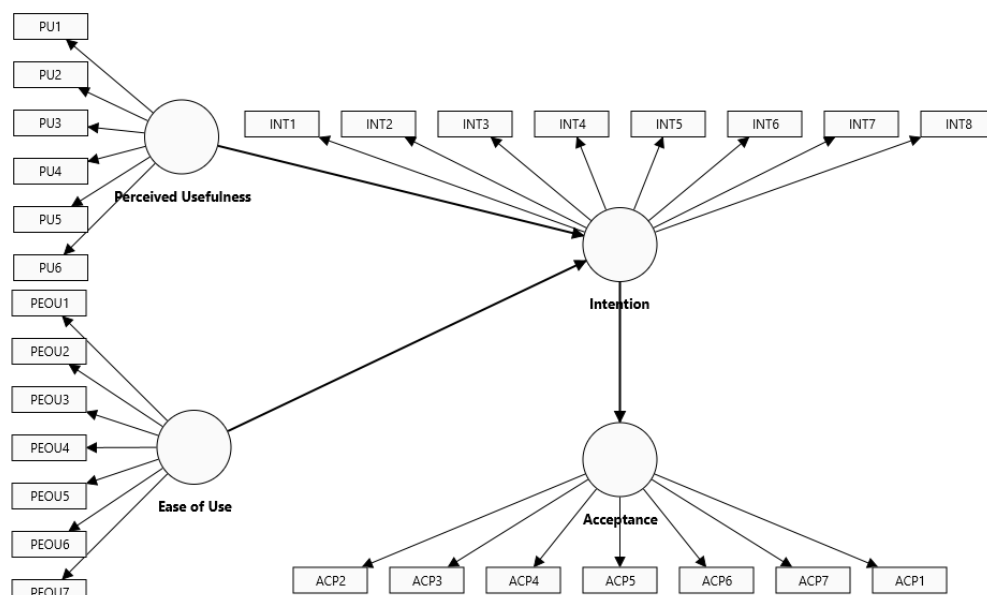


Fig. 1: Acceptance of AI in Higher Education Institution Model
(Source: Researchers' Analysis)

3.0 Methodology

This study is quantitative research whereby data is collected and analyzed statistically to answer the research objectives and questions. This research gained 383 participants among students and academicians in higher education institutions around Malaysia. A convenience sampling technique was utilized where subjects were selected because they were easily accessible to the researcher. This method allowed for quickly and easily gathering data with minimal cost and effort. A survey questionnaire was conducted and distributed electronically and face-to-face to the respondents. The questionnaire encompasses four sections. In section A, seven questions on the basic demographic profiles were asked. Section B discusses questions related to the acceptance of AI in higher education institutions. In addition, Section C discussed questions related to intention, ease of use, and perceived usefulness. Sections B and C used the Likert scale to allow respondents to respond appropriately to the question. The Likert scale used in the questionnaire is as follows: 1-Strongly Disagree, 2-Disagree, 3-Neutral, 4-Agree, 5-Strongly Agree. This research applied SmartPLS to analyze the data and test the hypotheses.

Table 1 summarizes the respondents' demographic profiles. According to the table, the majority of the respondents are female (56.7%) and male (43.3%). Most of the respondents were aged between 22 and 25 (77.5%), followed by those aged 18 to 21 (20.9%) and 26-30 (1.6%). In addition, most respondents were full-time students or staff (99.2%), while part-time students or staff comprised only 0.8%.

Table 1. Demographic Profiles

Demographic Factor	Category	Frequency (N)	Percentage (%)
Gender	Male	166	43.3
	Female	217	56.7
Age	18-21	80	20.9
	22-25	297	77.5
	26-30	6	1.6
Mode of Study/Work	Full-time	380	99.2
	Part-time	3	0.8
Academic Institution	University of Technology Mara (UiTM)	356	93.0
	Universiti Teknikal Malaysia Melaka (UTEM)	6	1.6
	International Islamic University Malaysia (IIUM)	4	1.0
	Universiti Sains Islam Malaysia (USIM)	4	1.0
	Universiti Utara Malaysia (UUM)	4	1.0
	Universiti Putra Malaysia (UPM)	2	0.5
	Universiti Pendidikan Sultan Idris (UPSI)	2	0.5
	Universiti Poly-Tech Malaysia (UPTM)	3	0.8
	Universiti Kebangsaan Malaysia (UKM)	2	0.5
Faculty	Faculty of Business and Management	239	62.4
	Faculty of Accountancy	22	5.7
	Faculty of Civil Engineering	12	3.1
	Faculty of Applied Sciences	17	4.4
	Faculty of Architecture, Planning & Surveying	5	1.3
	Faculty of Computer and Mathematical Sciences	6	1.6
	Faculty of Education	23	6.0
	Faculty of Health Sciences	31	8.1
	Faculty of Hotel and Tourism Management	19	5.0
Education Level	Faculty of Syariah and Law	9	2.3
	Diploma	19	5.0
	Degree	356	93.0
	Master	5	1.3
How frequently do you use AI tools in learning/teaching?	PhD	3	0.8
	Less than 2 hours	156	40.7
	2 hours	161	42.0
Total	8 hours and above	66	17.2
		383	100

4.0 Findings and Discussion

Due to the study's predictive nature and formative measurement (Hair et al., 2019), the researcher employed Smart Partial Least Squares (PLS) to test its hypothesis.

4.1 Common Method Bias

Standard method bias (CMB) may introduce a confounding factor in the study if the data were gathered solely from one source (Halimi et al., 2021). To address this problem, the researchers utilized a statistical method by doing a comprehensive collinearity study. Collinearity may be problematic if the Variance Inflation Factor (VIF) exceeds 3.3. The findings of the collinearity analysis in the present study indicate that all the VIF values were below 3.3 (Table 2), suggesting that there is no significant issue of single-source bias with the existing data.

Table 2. Full Collinearity Testing

Construct	PU	PEOU	INT
VIF	2.855	2.855	1.000

Note: PU = Perceive Usefulness; PEOU = Perceived Ease-of-use; INT = Intention

4.2 Measurement Model

The researchers utilized a two-step methodology involving measuring and constructing a structural model (Hafaz Ngah et al., 2020). Before advancing to the structural model, the researchers constructed a measuring model that included convergent and discriminant validity (Albtoosh & Ngah, 2022; Hair et al., 2019). Convergent validity is the assurance that all items accurately and consistently measure the particular concept they are intended to test. Convergent validity is established when the loading and the average variance extracted (AVE) are equal to or more than 0.5 and when the composite reliability is equal to or greater than 0.7. Table 3 demonstrates that the loadings, AVEs, and CR are all above the threshold values advised by Hair et al. (2019). The results affirm that the study has successfully established convergent validity.

Table 3. Measurement Model

Construct	Items	Loadings	CR	AVE
Acceptance	ACP1	0.826	0.947	0.717
	ACP2	0.850		
	ACP3	0.871		
	ACP4	0.857		
	ACP5	0.850		
	ACP6	0.803		
	ACP7	0.869		
Ease of Use	PEOU1	0.806	0.942	0.698
	PEOU2	0.798		
	PEOU3	0.833		
	PEOU4	0.808		
	PEOU5	0.867		
	PEOU6	0.877		
	PEOU7	0.858		
Intention	INT1	0.832	0.948	0.693
	INT2	0.852		
	INT3	0.810		
	INT4	0.824		
	INT5	0.882		
	INT6	0.840		
	INT7	0.792		
	INT8	0.826		
Perceived Usefulness	PU1	0.886	0.942	0.730
	PU2	0.850		
	PU3	0.862		
	PU4	0.846		
	PU5	0.831		
	PU6	0.851		

Secondly, the researchers assessed the discriminant validity to confirm that the items used to measure a particular construct differed from other constructs in the research framework. The HTMT criterion was used to evaluate discriminant validity. The HTMT values should be ≤ 0.85 , the stricter criterion and the mode lenient criterion should be ≤ 0.90 . Table 4 demonstrates that all the HTMT values were below the more stringent threshold of < 0.85 . This confirms that the respondents comprehended the unique nature of the four constructs, and there were no concerns with discriminant validity in the study.

Table 4. Discriminant Validity

	Acceptance	Ease of Use	Intention	Perceived Usefulness
Acceptance				
Ease of Use	0.803			
Intention	0.807	0.843		
Perceived Usefulness	0.771	0.762	0.819	

4.3 Structural Model

The study used a bootstrapping technique with 5000 subsamples to test the direct effect of the study. A hypothesis can be supported if the beta value direction is parallel with the hypothesis, $t\text{-value} \geq 1.645$, $p\text{-value} \leq 0.05$, and the confidence interval has no zero value

between the lower and upper levels (Hair et al., 2019). Meanwhile, for effect size, 0.02 is classified as a small effect size, 0.15 is medium, and 0.35 and above is a large effect size. The result for the direct hypothesis was that all the hypotheses were supported. H1 and H2 were supported, confirming that perceived ease-of-use ($\beta = 0.286$, $p < 0.01$) and perceived usefulness ($\beta = 0.628$, $p < 0.01$) have a positive relationship with intention to use AI. With two predictors, R2 for intention was 0.765, indicating that perceived ease of use and perceived usefulness explained 76.5% of the variance in intention. Meanwhile, H3 was also supported with ($\beta = 0.850$, $p < 0.01$), suggesting that intention positively correlates with acceptance of AI in higher education institutions. Overall, the intention to use AI explains a 72.2% variance in acceptance with a large effect size. Table 5 and Fig. 2 illustrate the results of the direct hypotheses of the study.

Table 5. Hypotheses Testing

Hypothesis	Relationship	Std Beta	Std Error	t-value	p-value	BCI LL	BCI UL	f ²
H1	Ease of Use -> Intention	0.286	0.278	3.522	0.000	0.133	0.437	0.122
H2	Perceived Usefulness -> Intention	0.628	0.635	7.748	0.000	0.471	0.780	0.586
H3	Intention -> Acceptance	0.850	0.850	43.370	0.000	0.810	0.886	2.593

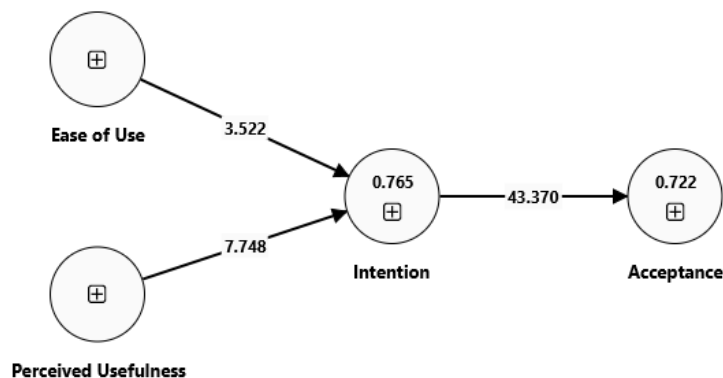


Fig 2. Path Coefficient Analysis

5.0 Conclusion and Recommendations

The results of this study confirm that the perceived ease of use (PEOU) and perceived usefulness (PU) play crucial roles in influencing the inclination to adopt artificial intelligence (AI) among higher education professors and students. According to the Technology Acceptance Model (TAM), both Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) were identified as important factors in predicting the desire to employ AI technology in educational environments. When AI tools are seen as user-friendly and advantageous for improving teaching and learning outcomes, educators and students are more inclined to have a favorable inclination to adopt these technologies.

Furthermore, this study emphasizes that the aim to utilize artificial intelligence (AI) substantially impacts the general adoption of AI in higher education. There is a direct correlation between the level of intention to employ AI and the probability of acceptance and integration of AI into educational practices by both academicians and students. This association highlights the need to promote favorable views toward AI by guaranteeing that AI technologies are easy to use and effective in accomplishing educational objectives. Recent research underscores the importance of Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) in AI acceptance within education. Zhang et al. (2021) reported similar effects on students adopting AI learning platforms. To encourage AI integration in education, institutions should focus on enhancing these perceptions.

However, the study is limited in scope to students with bachelor's degrees, Faculty of Business and Management at Universiti Teknologi MARA (UiTM). As such, the findings may not be fully generalizable to students from other UiTM faculties or those in other higher education institutions in Malaysia. The focus on business and management students may also introduce bias, as their exposure, attitudes, and perceptions toward Artificial Intelligence (AI) may differ from those in more technically oriented faculties such as Engineering or Computer Science. Therefore, caution should be exercised when extrapolating the results to a broader student population. Therefore, future research should consider expanding the study population to include students from various faculties and academic disciplines within UiTM and other public and private universities in Malaysia. A comparative analysis between students from business, science, technology, and humanities backgrounds may provide deeper insights into how academic orientation influences AI acceptance. Additionally, incorporating perspectives from faculty members and administrative staff could offer a more holistic understanding of AI integration in higher education.

Acknowledgments

The authors would like to sincerely thank the members of the study and the Faculty of Business and Management, Universiti Teknologi MARA Puncak Alam campus, for the opportunities given to complete this research.

Paper Contribution to Related Field of Study

This research contributes to the growing body of knowledge by applying the Technology Acceptance Model (TAM) to investigate the key factors affecting the acceptance and use of AI technologies among faculty, students, and administrators in higher education. This study contributes empirical evidence by collecting data from diverse higher education stakeholders, including students, academicians, and administrators.

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