Adoption of Artificial Intelligence-Powered Software among Technical Institution Students

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ABSTRACT

The rapid advancement of artificial intelligence (AI) has led to its widespread adoption across various fields, including education. This study investigates the factors influencing the adoption of AI software among undergraduates at one of the technical universities in Malaysia. A quantitative research design was employed, utilizing a structured questionnaire to collect data from a sample of 370 undergraduate students. Data analysis was conducted using IBM SPSS Statistics. The results revealed that performance expectancy, effort expectancy, social influence, and facilitating conditions significantly influence the adoption of AI software among undergraduate students. These findings provide valuable insights into the determinants of AI adoption in higher education, which can inform strategies to enhance educational technology integration.

Keywords: Artificial Intelligence; Technology Adoption; TVET; education; UTAUT.

INTRODUCTION

Technical and Vocational Education and Training (TVET) in higher learning institutions play a crucial role in shaping the workforce nationwide. The higher learning institutions for TVET include universities, colleges, and polytechnics that offer a range of academic programs that equip students with theoretical knowledge and practical skills, alongside hands-on and technical skills necessary for specific trades and industries for preparing the students for various professional careers. Adaptation to the changes brought by Industrial Revolution (IR) 4.0 is essential (Ellahi et al., 2019). The integration of IR 4.0 technologies in teaching and learning can enhance the educational experience, making it more relevant to the needs of modern industries (Masood et al., 2024). It also prepares TVET students to thrive in a rapidly changing job demand where digital literacy, critical thinking, and technical skills are the ultimate (Siti et al., 2023).

One of the IR 4.0 technologies that is relevant to the educational industry is artificial intelligence (AI). AI has been applied to most computer programs and systems that perform more complex and demanding tasks than average computer programs (Jun et al., 2024). AI capabilities are now widely used in various fields and have transformed how people live, work, and communicate (Umar Baki et al., 2023). AI-powered software is designed to solve complex problems, make predictions, and automate various tasks, making them more valuable in various disciplines including educational settings (Wilson & Syed, 2021). AI could transform the education landscape and significantly enhance students' learning outcomes (Hashim et al., 2022; Kaur, 2021; Mohamud et al., 2023). Additionally, AI is increasingly popular due to its numerous benefits including enriching the student learning experience, impacting and improving educational efficiency in the way education is delivered and accessed, able to identify students learning patterns for more exclusive personalized learning experiences (Jun et al., 2024; Mohamud et al., 2023).

Although the increasing popularity of AI in education and the advancements in AI technology have progressed significantly, studies on the perception of adoption of AI technology among undergraduate levels, especially at TVET institutions remain limited. A study reported that majority of the students were having moderate to less awareness and knowledge in AI (Mansor et al., 2022). Therefore, a study on the adoption of AI technology, especially among TVET's undergraduates should be conducted.

Based on previous studies related to technology adoption, mixed and inconsistent findings are reported. Several studies informed that performance expectancy, effort expectancy, social inclusion and facilitating condition were essential and significant (Taufiq Hail et al., 2024; Trang et al., 2024), meanwhile some studies reported that facilitating condition was not significant but the other three components were significant (Camilleri, 2024; Gajić et al., 2024; Pande & Taeihagh, 2024). Furthermore, study by Shahid et al. (2024) reported that only performance expectancy, effort expectancy and facilitating condition were significant, but social inclusion was not significant. However, studies by Sun et al. (2024) and Hernandez et al. (2023) reported only performance expectancy significant to the technology adoption. Due to inconsistent finding on the factors that influence technology adoption, hence this study was conducted to figure out the framework of AI adoption among TVET students.

This study aimed to assess the significance of technology adoption variables using UTAUT, i.e., performance expectancy; effort expectancy; social influence; and facilitating conditions for adopting AI-powered software among TVET's undergraduates.

LITERATURE REVIEW

(Times New Roman, 12 pt, Bold, All Caps) The integration of AI technologies has the potential to revolutionize teaching and learning practices, enhancing student engagement, personalization, and skill development (Hashim et al., 2022; Kaur, 2021; Mansor et al., 2022; Mohamud et al., 2023). Understanding the factors that influence the acceptance and use of AI technologies is crucial for successful implementation in educational settings. This section informs the scholar's reviews regarding AI and technology adoption.

2.1 AI-powered Software

AI-powered software is a branch of computer science programs that have been designed to perform tasks that would typically require human intelligence (Stöhr et al., 2024). AI software is a computer program involving machine learning, natural language processing, and other technologies that can allow the software to complete tasks such as analysing and interpreting vast amounts of data, making decisions or even making predictions (Chowdhury, 2018). These programs will also learn from experience and adapt to new situations thus making them always effective over time.

AI-powered software programs can be categorized into Natural Language Processing (NLP) Programs, Machine Learning (ML) Programs, robotics programs, cognitive computing programs, deep learning programs, computer vision programs, predictive analytics programs, virtual agents and chatbots (Stöhr et al., 2024). These programs are designed to learn and adapt to new data thus enabling them to perform tasks such as image recognition, give recommendations, make predictions about future events or trends, simulate conversation, provide customer service and even help in writing essays or scripts (Kaur, 2021; Taufiq Hail et al., 2024).

AI-powered software eases organizations in many ways and impacts the organizations to be more efficient, productive, and profitable (Stöhr et al., 2024). Besides, in the education sector, one of the most significant applications of AI-powered software programs is automated grading software (Xuan & Yunus, 2023). The traditional method of grading needs a teacher or lecturer to spend several hours grading papers and assigning grades. With the help of AI-powered software programs, it will save the lecturer's time and increase accuracy. AI-powered software programs can also provide personalized learning opportunities for students. These programs can analyze student learning patterns and identify areas where they need more support (Hashim et al., 2022).

2.2 Adoption of AI

In recent years, the integration of AI in education has been recognized as an approach to transform traditional teaching and learning practices into more digitalization ways (Kaur, 2021). AI-powered software programs have the potential to support educators in delivering personalized instruction, identifying individual learning needs, and facilitating adaptive learning experiences (Xuan & Yunus, 2023). These technologies can analyze large amounts of data, such as student performance records and learning preferences. Numerous studies have examined the factors influencing the adoption of AI technologies in educational settings, particularly among undergraduate students. One key factor is the potential benefits that AI can bring to student engagement and academic outcomes (Trang et al., 2024).. Moreover, AI can offer real-time feedback and guidance, enabling students to monitor their progress and make necessary improvements. However, apart from the potential advantages, the adoption of AI in undergraduate education remains relatively low (Mansor et al., 2022). Several barriers and challenges have been identified in literature. One of the challenges is the perceived complexity and technical requirements for AI-powered software (Camilleri, 2024). Students may lack the necessary skills or knowledge to effectively use these technologies, leading to resistance to adoption (Gajić et al., 2024). Therefore, this section presents an overview of the adoption of AI-powered software programs in undergraduate education, emphasizing the role of the UTAUT framework. It discusses the potential benefits and challenges associated with integrating AI technologies into the learning environment, and it explores how the UTAUT model can help elucidate the factors influencing the acceptance and use of AI among undergraduate students. The review examines studies that have investigated the impact of AI on student engagement, personalized learning, and skill development, specifically through the lens of UTAUT.

2.3 Theory in Adoption

Technology adoption refers to the process through which individuals or organizations accept innovations into their existing practices, systems, or daily lives (Sharma & Mishra, 2014). It involves decision-making and behavioral changes. However, the adoption of technology typically follows a series of stages or steps, including awareness, interest, evaluation, trial, and adoption or rejection. During these stages, individuals will be affected by some potential aspects such as benefits, peer influence, and risks of adopting new technology (Junior et al., 2019). They may gather information, seek recommendations, and evaluate the technology.

Theory of adoption explains how new ideas, products, or technologies are adopted and spread within a social system. Due to this research focusing on understanding the psychology of user acceptance, there is a brief explanation for the UTAUT model.

The Unified Theory of Acceptance and Use of Technology (UTAUT) is a theoretical framework that is used to explain and predict individuals' acceptance in the term of technology (Venkatesh & Bala, 2008). It was developed by combining and extending several existing models of technology acceptance such as Theory of Reasoned Action (TRA) and Theory of Planned Behavior (TPB) (Venkatesh et al., 2003). There are four direct determinants in UTAUT, namely Performance expectancy, Effort expectancy, social influence, and Facilitating condition, follows by four moderating factors such as age, gender, experience, and voluntariness. However, this paper only reported the assessment on the direct determinants.

Performance Expectancy

Performance expectancy is defined as the extent to which technology will help the individual perform better. It includes perceived usefulness, motivation to use, job-fit, relative advantage over previous systems and expectations of the outcome while using the technology. This indicates that knowledge and control of the system are included in this construct through the perceived usefulness (Venkatesh et al., 2003).

A study by Ali et al. (2024) investigated the implementation of an e-learning system for pre-university students. The findings show that performance expectancy was significant in adopting the e-learning system. In addition, performance expectancy was influencing digital learning adoption among Cambodian university students (Ly et al., 2024). Similarly, performance expectancy significantly influence the adoption of ICT by Moroccan nursing students (Sari et al., 2024). However, performance expectancy was not significant in adopting virtual learning among developing countries, yet significant in developed countries (Monteiro et al., 2022). Due to inconsistent findings of the influence of performance expectancy in adoption of technology in education setting, thus this study hypothesizes as the following:

H1: Performance expectancy has a significant relationship to the adoption of artificial intelligence powered software among TVET undergraduates.

Effort Expectancy

Effort expectancy is defined as the user's ease of operating a system, which includes the perceived ease of use and complexity of a system (Venkatesh et al., 2003). Chan (2022) conducted a study investigating the factors influencing consumers' adoption of Open Banking, based on UTAUT model. The researchers collected data from 456 Australian survey respondents. Effort expectancy was found significantly influence an intention to adopt open banking. Wu (2021) conducted a study to identify the factors that influence bank customers' intention and attitude toward using mobile chat. The findings indicate that reachability and convenience influence performance expectancy, while effort expectancy is influenced by all three technological characteristics (mobility, reachability, and convenience). Moreover, Effort expectancy was identified as a driving factor that influences both utilitarian and hedonic performance expectancy of mobile shopping services (Yang, 2010). The study presented the key factors influencing US consumers' intentions to use mobile shopping services. Zhu (2023) conducted a study to understand consumers' usage of smart wearable devices and their potential for interactive marketing. The findings reveal that consumer innovativeness indirectly affects smart wearable device usage through effort expectancy. Additionally, the study finds that experienced consumers are less sensitive to performance expectancy but more influenced by effort expectancy when it comes to smart wearable devices. Due to most studies find effort expectancy significantly influences technology adoption, therefore, this study hypothesizes the following:

H2: Effort expectancy has a significant relationship with the adoption of artificial intelligence-powered software programs among TVET undergraduates.

Social Influence

Social influence is defined as the degree to which an individual believes that others can use the system, which captures the beliefs of people that others would benefit from the use of the system (Venkatesh et al., 2003). It examines research that investigates the impact of social factors, such as peers, faculty, and institutional support, on technology acceptance and use. Gao (2019) has conducted a study to examine the adoption of bike sharing systems in China. The data were collected through a survey of 298 bike sharing system users in China. However, in the finding, social influences were not found to have a significant positive impact on users' behavioral intention to use bike sharing systems. Farah (2018) has conducted a study to examine the factors that influence consumer intention and use behavior in the adoption of mobile banking. A questionnaire was used to collect data from 490 respondents in Pakistan, who rated their responses on a five-point Likert scale. The findings of the study show that social influence such as peer influence and family influence is significant in influencing usage behavior.

The pattern of influence of social influence on continuance intention has changed (Lu, 2019). In the study of knowing the impact of personal innovativeness in information technology (PIIT) and social influence on user continuance intention toward mobile commerce, researcher has provided these valuable insights. Due to inconsistent findings of the influence of social influence in adoption of technology, thus this study hypothesizes as the following:

H3: Social influences have a significant relationship to the adoption of artificial intelligence powered software programs among TVET undergraduates.

Facilitating Conditions

Facilitating conditions is defined as the extent to which an individual believes that the supporting infrastructure is

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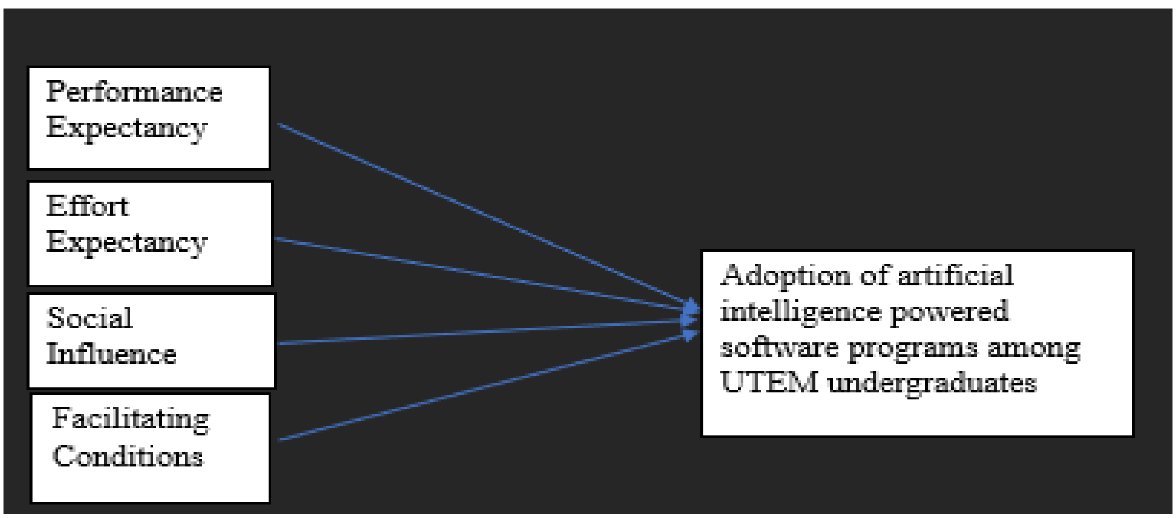
available to support the adoption of the system (Venkatesh et al., 2003). It explores research that examines the role of facilitating conditions, such as access to resources, technical support, and organizational infrastructure, in promoting the successful adoption and use of technology. Alomari (2022) has examined the factors influencing trust in mobile government (m-government) in Jordan, a developing country. The study applies the unified theory of acceptance and use of technology (UTAUT) as a theoretical. A survey was conducted among 510 young Jordanian citizens who had internet access and used smartphones. The finding shows a significant result between facilitating conditions and trust in accepting the technology. Azam (2019) has conducted a study to examine the diffusion of information and communications technology (ICT) among small and medium enterprises (SMEs). The findings reveal the facilitating conditions are found to influence expectations and ICT use.

However, there is no significant relationship between facilitating conditions and intention to use an enterprise resource planning system (Keong, 2022). Due to inconsistent findings of the influence of facilitating condition in adoption of technology, thus this study hypothesizes as the following:

H4: Facilitating conditions has a significant relationship to the adoption of artificial intelligence powered software programs among TVET undergraduates.

2.3 Theoretical Framework

The extensive literature review based on previously described formed a conceptual model for this study. There were four direct determinants that influence the adoption of artificial intelligence-powered software among undergraduates. The dimensions of the independent variables in this study are performance expectancy, effort expectancy, social influence and facilitating conditions. This study's dependent variable was undergraduates' adoption of artificial intelligence-powered software program.



METHOD

This study tested a hypothesized structural model. Moreover, the present study has developed hypotheses based on literature and existing theories. Since the study tested hypotheses, the study uses a deductive research approach. Besides, the study adopted positivism for research philosophy. This study applied explanatory research purpose which employed a quantitative research method. Since this study requires more than one respondent to collect quantitative data, the technique for collecting quantitative data in this study was a survey questionnaire. Besides, the study employed a cross-sectional as the time horizon, which the collection of data occurs at a single point in time. Moreover, cross-sectional offers advantages in saving time and cost. Therefore, this study employed a cross-sectional time horizon. Studies using a sample will produce better and more reliable results. The population in this study is the TVET undergraduates among the University Technical Malaysia Malacca (UTEM). This study used a random sampling design to put the population smaller into sample where each of the members in the population

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has the same chance of being selected as a respondent. Based on the UTEM report on 1st January 2024 by UTEM official website, there were 12201 undergraduate students in UTEM. Therefore, according to Table Krejchie and Morgan, the minimum sample size for this study was 370. The survey was designed to address and achieve the research questions and objectives, drawing on previous studies by other researchers. Measurement scales validated in existing literature were used, with responses recorded on a Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The data collected online, were analyzed using SPSS version 25 for a reliability and validity analysis, Pearson Partial correlation, and multiple regression tests to meet the study's objectives.

RESULTS AND DISCUSSION

Researchers conducted a reliability analysis for the collected data. It involves 24 items including independent variables and dependent variables in the study.

Table 1

Case Processing Summary			
		N	%
Cases	Valid	370	100.0
	Excluded[a]	0	.0
	Total	370	100.0

Table 2

Reliability Statistics	
Cronbach's Alpha	N of Items
.839	24

Table 1 and Table 2 provided case processing summary and reliability statistics respectively. According to Table 1, the number of valid respondents was 370 and no items were excluded. In Table 2, it shows that Cronbach’s Alpha for 310 respondents and 24 number of items result in a value of 0.839. According to (Tavakol, 2011), Cronbach’s Alpha with the value greater than 0.70 are considered acceptable. For this study, the Cronbach Alpha is considered as “Good” due to the value is greater than 0.8. Therefore, all items in independent variable and dependent variable had a good internal consistency and reliability.

Table 3 Pearson's Partial Correlation for Each Variable

Correlations						
		PE	EE	SI	FC	DV
PE	Pearson Correlation	1	.660**	.632**	.573**	.743**
	Sig. (2-tailed)		.000	.000	.000	.000
	N	370	370	370	370	370
EE	Pearson Correlation	.660**	1	.690**	.564**	.656**
	Sig. (2-tailed)	.000		.000	.000	.000
	N	370	370	370	370	370
SI	Pearson Correlation	.632**	.690**	1	.620**	.702**
	Sig. (2-tailed)	.000	.000		.000	.000
	N	370	370	370	370	370
FC	Pearson	.573**	.564**	.620**	1	.718**

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	Correlation					
	Sig. (2-tailed)	.000	.000	.000		.000
	N	370	370	370	370	370
DV	Pearson Correlation	.743**	.656**	.702**	.718**	1
	Sig. (2-tailed)	.000	.000	.000	.000	
	N	370	370	370	370	370
**. Correlation is significant at the 0.01 level (2-tailed).						

Table 3 shows the analysis results of Pearson's Partial Correlation. It involves performance expectancy, effort expectancy, social influence and facilitating conditions and dependent variables which was adoption of AI-powered software program. From the result above, all independent variables have a strong positive significant relationship with the dependent variable.

Table 4 Coefficients of Multiple Linear Regression Analysis

Coefficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.916	.220		4.167	.000
	PE	.229	.048	.208	4.822	.000
	EE	.388	.042	.423	9.337	.000
	SI	.082	.022	.155	3.730	.000
	FC	.096	.037	.123	2.635	.009

Based on Table 4, the significance value for all variables; performance expectancy, effort expectancy, facilitating condition, and social influence, were less than 0.05. It shows that performance expectancy had a positive relationship towards the adoption of AI-powered software program among TVET undergraduates, effort expectancy had a positive relationship towards the adoption of AI-powered software program among TVET undergraduates, social influence had a positive relationship towards the adoption of AI-powered software program among TVET undergraduates, and facilitating conditions had a positive relationship towards the adoption of AI-powered software program among TVET undergraduates . The linear equation was developed as below:

Y=0.916+0.229 X_1+0.388 X_2+0.082X_3+ 0.096 X_4

Where Y= Adoption of AI-powered software program

X_1 = Performance Expectancy,

X_2 = Effort Expectancy,

X_3 = Social Influence,

X_4= Facilitating Conditions

CONCLUSION

The finding showed that performance expectancy, effort expectancy, social influence, and facilitating conditions scored a p-value of 0.000 and 0.009, which is lower than 0.05. According to the multiple regression analysis, p-value which is lower than 0.05 is having a significant relationship with dependent variable. The finding also revealed that effort expectancy contributing the most affecting the adoption of AI-powered software program. Respondents prefer clear and easy instruction to control and use the AI-powered software program. In other words, the less technical knowledge needed to use AI-powered software, the more they will adopt. Respondents also believe that AI-powered software programs increase their learning productivity and help them get good grades. There are some limitations in this research, such as limited time and location. Therefore, future research may take a longer time to gain a better result. Apart from that, the setting of the study also can use qualitative methods to gain deeper insights among TVET students. A comparison study also should be done to see differences between TVET and non TVET undergraduates in adopting AI.

REFERENCES

1. Abbad, & M., M. M. (2021). Using the UTAUT model to understand students’ usage. Education and Information Technologies, 7205-7224.
2. Ajzen. (1991). The Theory of Planned Behavior model.
3. Boateng, A. B. (2022). Technology appropriation in Higher Education: The case of Communication Educators in Ghana. Integrated Journal for Research in Arts and Humanities.
4. Bryant, J. (2020, Jan 14). How artificial intelligence will impact K-12 teachers. Retrieved from mckinsey: https://www.mckinsey.com/industries/education/our-insights/how-artificial-intelligence-will-impact-k-12-teachers
5. Burke, A. (2020). Ultracapacitors: why, how, and where is the technology. Journal of Power Sources, 37-50.
6. Campbell, S., Greenwood, M., & Prior, S. (2022). Purposive sampling: complex or simple? Research case examples. Journal of research , 1714.
7. Carmines, E. G., & Zeller, R. A. (1979). Reliability and Validity Assessment. Reliability and Validity Assessment.
8. Cham, T.-H. (2022). Digitalization and its impact on contemporary marketing strategies and practices. Journal of Marketing Analytics.
9. Chua, P. Y. (2018). Elucidating social networking apps decisions: Performance expectancy, effort expectancy and social influence. Nankai Business Review International, 118-142.
10. Dulle, F. W. (2021). The suitability of the Unified Theory of Acceptance and Use of Technology (UTAUT) model in open access adoption studies. Sage journal.
11. Ebert, R. J., & Piehl, D. (1973). Time Horizon: A Concept for Management. Sage journal, 49-59.
12. Elbanna, S. (2023). Exploring the integration of ChatGPT in education: adapting for the future. Management & Sustainability: An Arab Review.
13. Keong, M. L. (2022). Explaining intention to use an enterprise resource planning (ERP) system: an extension of the UTAUT model. Business Strategy Series, 173-187.
14. Tavakol, M. (2011). Making sense of Cronbach's alpha. International journal of medical education.