

AI Integration in TVET: Examining Educators' Behavioral Intentions and the Moderating Role of Experience

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Abstract: Artificial Intelligence (AI) is a branch of contemporary science and information technology that aims to replicate human-like intelligence in machines. Its application has increasingly become a significant component in modern education, transforming the way knowledge is accessed and delivered. Educators are now required to recognize AI technology as a pivotal tool in both current and future educational environments. In light of this, the present study investigates the predictors of behavioral intention, namely, performance expectancy, effort expectancy, social influence, and facilitating conditions, towards the use of AI technology among lecturers in Polytechnics and Community Colleges (POLYCC) in Malaysia. This research is grounded in the Unified Theory of Acceptance and Use of Technology (UTAUT) framework. Employing a simple random sampling method to ensure equal representation, data were collected from 142 academic staff members in POLYCC through an online questionnaire. The data were analyzed using SPSS to test the proposed research model and hypotheses. Findings revealed that performance expectancy, effort expectancy, and facilitating conditions significantly and positively influence lecturers' behavioral intention to use AI. In contrast, social influence did not have a significant effect. Additionally, the study identified experience as a moderating variable, which significantly strengthened the relationships between effort expectancy, social influence, and facilitating conditions with behavioral intention. These results highlight the importance of considering educators' experience levels when designing strategies for AI adoption in teaching and learning environments.

Keywords: *Artificial Intelligence, Behavioral Intention, UTAUT Theory, TVET*

1. Introduction and Background

The adoption of artificial intelligence (AI) is a growing global trend, and Malaysia is actively participating in this movement. The use of AI technologies in Malaysia is expanding rapidly, with more companies exploring and integrating AI to support business growth. According to a study by the IBM Malaysia Business Value Institute, one-third of surveyed companies have adopted generative AI, setting new benchmarks for innovation and success. This reflects the crucial role of AI in promoting innovation, supporting economic recovery, and reducing the digital divide. Holmström (2022) emphasized that the successful implementation of AI technologies significantly influences organizational performance. In response to these developments, the Malaysian government introduced the Malaysia National Artificial Intelligence Roadmap 2021-2025 (Ministry of Science, Technology and Innovation, 2023). This initiative aims to guide the responsible and ethical use of AI, with the broader goal of enhancing employment, competitiveness, innovation, and quality of life. The roadmap also seeks to promote sustainable economic growth through effective AI governance and implementation.

In the age of artificial intelligence (AI), lecturers need to adapt to new teaching environments and changing social conditions. More digital tools are being introduced into classrooms, and both lecturers and students must learn how to use them effectively. AI in education offers great potential to solve current challenges and improve the overall learning experience. Advancements in AI and smart technologies are expected to play an important role in shaping the future of higher education. The use of Artificial Intelligence in Education (AIED) is likely to transform teaching and learning processes in universities and colleges (Hwang et al., 2020; Luan et al., 2020). Meanwhile, Pelletier et al. (2023), in the Horizon Report 2023, also identified AI as a key technology for teaching and learning in higher education. AI may also impact how higher education institutions are managed and organized. The Ministry of Higher Education (MOHE) views AI as a useful tool to improve learning in Malaysia. To support this, the Director General of the Polytechnic and Community College Department issued

a directive on 17 April 2023 encouraging the use of AI to maintain the quality of teaching. The Malaysian Qualifications Agency (MQA), in Advisory Note 2/2023, also recommended including AI skills in study programs, so students are better prepared for future careers.

Artificial Intelligence (AI) is becoming more important in Technical and Vocational Education and Training (TVET), as it can help improve teaching by reducing teachers' workload (Bryant et al., 2020). Although some TVET institutions are already using AI and robotics, many educators still do not fully understand the skills needed to use these technologies effectively (Benvenuti et al., 2022). Implementing AI is not easy, and many institutions face difficulties and fail to adopt it successfully (Alhwaiti, 2023). A study by Park and Kwon (2023), found that teachers in Korea were more interested in real-life uses of AI than in learning the basic concepts. This suggests that while TVET educators want to use AI for practical teaching, they may lack knowledge of how AI works. To use AI effectively in TVET, educators need a better understanding of the technology. Challenges such as technical issues, low student engagement, privacy concerns, and confusion about how to use the tools can make adoption difficult (Raffaghelli et al., 2022). According to Jain et al. (2022), fear of change, lack of training, uncertainty, and low trust in AI also make educators hesitant to use it. Many TVET educators still do not understand how to use generative AI in their teaching strategies (Zahri et al., 2023). This lack of knowledge can prevent them from using AI effectively. Because of this, more research is needed to understand what influences their willingness to use AI, including the causes and related theories. Currently, there is limited research on this topic in Malaysian TVET institutions. Therefore, this study aims to identify the key factors that affect TVET educators' intention to use AI in their teaching.

2. Literature Review

Behavioral intention refers to the conscious plan or resolve to perform or avoid a specific action in the future, and it strongly predicts actual technology use (Warshaw & Davis, 1985; Venkatesh et al., 2008; Venkatesh et al., 2003). The Unified Theory of Acceptance and Use of Technology (UTAUT) is widely employed to examine intentions and adoption among different user groups, especially in educational and AI contexts.

For instance, Ragheb et al. (2022) applied the UTAUT model to examine factors influencing students' intentions to use chatbots in higher education. Their findings revealed that performance expectancy, effort expectancy, and social influence significantly affected students' behavioral intentions. Similarly, Kwak et al. (2022) investigated behavioral intentions toward AI-based healthcare technologies and reported that performance expectancy, effort expectancy, and self-efficacy were key predictors of positive user attitudes. In the higher education context, Chatterjee and Bhattacharjee (2020) highlighted that behavioral intention plays a critical role in the adoption of AI, indicating that acceptance of AI technologies is closely tied to users' willingness and readiness to integrate them into educational environments. Furthermore, Sergeeva et al. (2025) applied UTAUT2 to explore students' adoption of generative AI, finding that habitual use, performance expectancy, hedonic motivation, social influence, and price value significantly predicted behavioral intention.

Performance Expectancy

Performance expectancy refers to how much a person believes that using a new system will improve their job performance (Venkatesh et al., 2003). It includes perceived usefulness, job fit and expected outcomes factors that reflect how helpful the system is in supporting their work. According to Davis (1989), perceived usefulness is the belief that using a system will make tasks more efficient or improve results. In education, performance expectancy means that teachers believe AI can support their teaching, help them deliver lessons better, and improve student learning outcomes. AI is seen to offer benefits such as faster access to information, better communication, more flexible learning environments, and improved presentation of materials (Pantelimon et al., 2021).

Several studies support the importance of performance expectancy in encouraging technology use. Alhwaiti (2023) found that it positively affects teachers' confidence and well-being. Similarly, Ayaz et al. (2020) reported that performance expectancy is one of the strongest factors influencing people's decision to use AI. Srivastava and Singh Bhati (2020) also found that teachers who believe AI helps them perform better are more confident in using it for teaching.

These findings suggest that performance expectancy strongly influences the intention to use AI. Based on this, the following hypothesis is proposed:

H1: Performance Expectancy has a positive influence on the behavioral intention to use AI among TVET educators in Malaysia.

Effort Expectancy

Effort expectancy refers to how easy a person thinks it is to use a system (Venkatesh et al., 2003). It includes how simple, clear, and user-friendly the system is. In this study, it is expected that people with more experience using AI may not rely as much on how easy they think it is to use and instead focus on their experience. Liu et al. (2022) found that people are more likely to use a system if they think it is easy to use. Srivastava et al. (2020) also showed that ease of use influences people's intention to adopt new technology. Similarly, Anthony et al. (2023) reported that ease of use positively affects lecturers' willingness to use technology in teaching. However, not all studies agree. An et al. (2023) found that just being easy to use is not enough to make teachers want to use AI. This suggests that effort expectancy may not always predict behavior in the same way in different situations. Because of these mixed results, this study aims to better understand how effort expectancy influences educators' intention to use AI.

H2: Effort Expectancy has a positive influence on the behavioral intention to use AI among TVET educators in Malaysia.

Social Influence

The Unified Theory of Acceptance and Use of Technology (UTAUT) is defined as the extent to which individuals feel pressure from others, such as colleagues or their organization, to use new technology (Venkatesh et al., 2003). This influence can affect technology adoption in both voluntary and non-voluntary situations, where users may use the technology due to expectations rather than personal interest. Social influence includes how much people around the user, such as coworkers or supervisors, shape their perception of technology. Factors like age, gender, experience, and whether the use is voluntary can change how social influence works (Venkatesh et al., 2003).

Many recent studies support the idea that social influence affects technology adoption. Zhou et al. (2022) found that it has a positive effect on technology use. Ragheb et al. (2022) also reported that social influence encourages educators to use AI in higher education. Similarly, Kwak et al. (2022) found a strong relationship between social influence and intention to use AI. However, not all studies agree. Sabraz Nawaz et al. (2024) found that social influence had a weaker effect in some cases. These mixed findings suggest that more research is needed to better understand how social influence affects AI adoption in education.

H3: Social Influence has a positive influence on the behavioral intention to use AI among TVET educators in Malaysia.

Facilitating Conditions

Facilitating conditions refer to the support and resources, such as technical help and infrastructure, that make it easier for individuals to use a system (Venkatesh et al., 2003). These conditions can influence a person's willingness to use AI, especially when assistance is available if problems occur. While Venkatesh et al. (2003) suggested that facilitating conditions do not directly affect behavioral intention, they may become important when combined with factors like age and experience. However, studies in education have shown different results. For example, Chatterjee and Bhattacharjee (2020) found that strong support systems can encourage educators to adopt AI. Kwak et al. (2022) also showed that facilitating conditions have a direct, positive impact on the intention to use AI. Meanwhile, Alkhwalidi (2023) supported this, stating that the presence of proper resources helps increase acceptance of AI. These findings suggest that in higher education, support systems can influence educators' intention to use AI. Therefore, more research is needed to confirm these relationships in different settings.

H4: Facilitating Conditions have a positive influence on the behavioral intention to use AI among TVET educators in Malaysia.

Several theories about the moderation effect have been proposed based on the topics that have been presented before. A moderating variable has been proposed to study behavioral intention, which is experience. Venkatesh et al. (2003) studied user experience and found that the influence of effort expectancy, social influence, and

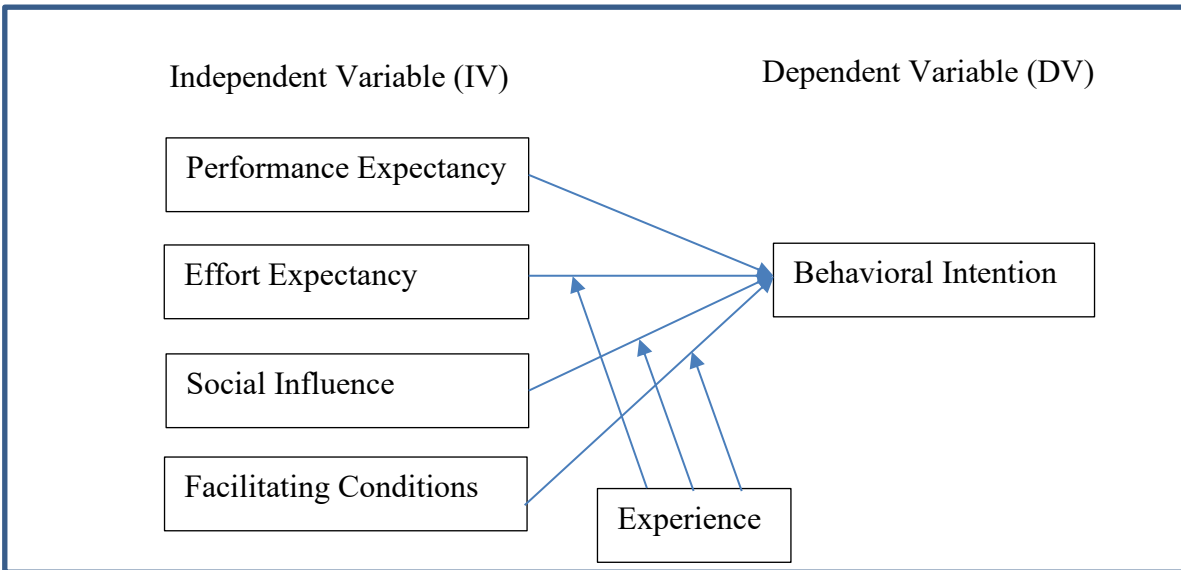
facilitation conditions on behavioral intention changes with the accumulation of use experience. Several hypotheses regarding the moderating effects have been developed as follows.

H5a: Experience moderates the relationship between effort expectancy and behavioral intention to use AI among TVET educators in Malaysia.

H5 b: Experience moderates the relationship between social influence and behavioral intention to use AI among TVET educators in Malaysia.

H5c: Experience moderates the relationship between facilitating conditions and behavioral intention to use AI among TVET educators in Malaysia.

Figure 1: Conceptual Framework



3. Research Methodology

This study adopts a quantitative research design using a structured questionnaire to examine the relationship between variables. A cross-sectional survey was conducted to collect data at a single point in time over several months. The study population consists of academic staff from Polytechnics and Community Colleges (POLYCC) across Malaysia. The focus on POLYCC academic staff is based on their relevance to the study's aim of exploring behavioral intentions to use AI in higher education. The sampling technique that is applied in this study is simple random sampling. Simple random sampling can be defined as a type of probability sampling. This sampling is the most frequently used because the selection of the audience is determined by chance (Salkind, 2018). In determining the minimum sample size for this study, G*Power software is employed. The researcher calculates the sample size by using G*Power 3.1.9.4. Thus, the setting measured in this study is as follows: Effect size f^2 : 0.15, $\alpha=0.05$, and the number of predictors = 5 (performance expectancy, effort expectancy, social influence, facilitating condition, and behavioral intention). The power was set at 95%. Thus, the sample size required for this study is 110.

This research study has received ethical approval from the Faculty Research Ethics Committee under the Faculty of Business and Management. Five constructs were measured in this study: performance expectancy, effort expectancy, social influence, facilitating condition, and behavioral intention. The constructs were measured using a five-point Likert scale ranging from 1, strongly disagree, to 5, strongly agree. Appropriate item modification was performed to fit the study context and validated by experts in the study area. A reliability test was conducted before the data collection to ensure the consistency of the measure. Based on the pilot test of 30 respondents, the internal consistency value for all constructs met the minimum requirement of 0.700. Meanwhile, to collect the data, an online survey was designed using Google Forms, and the invitation to participate in the study was sent through email and WhatsApp.

4. Results and Discussion

Data was analyzed using IBM SPSS Statistics version 26.0. Multiple regression analysis was conducted to examine the relationships between the study variables. Respondents were also required to provide demographic information to describe their background characteristics. The results of the demographic analysis are presented in Table 1.

Table 1: Demographic Profile of the Respondents (n=142)

Demographic Profile	Frequency	Percentage
Gender	49	34.5
Male		
Female	93	65.5
Age		
21-30 years	4	2.8
31-40 years	60	42.3
41-50 years	77	54.2
Over 51 years	1	0.7
Teaching Experience		
1-5 years	10	7.0
6-10 years	18	12.7
10-15 years	66	46.5
More than 15 years	48	33.8
States		
Federal Territory	14	9.9
Selangor	13	9.2
Melaka	11	7.7
Negeri Sembilan	15	10.6
Johor	13	9.2
Perak	9	6.3
Perlis	10	7.0
Kedah	12	8.5
Pulau Pinang	9	6.3
Pahang	12	8.5
Kelantan	6	4.2
Terengganu	7	4.9
Sarawak	6	4.2
Sabah	5	3.5

***Note: Frequency numbers are based on a total of 142 respondents**

Table 2: Demographic profile of use experience

Demographic Profile	Frequency	Percentage
Once or several times a day	70	49.3
Once a day	31	21.8
Once a week	27	19.0
Once a month	8	5.6
Once a year	2	1.4
Never	4	2.8
Total	142	100.0

According to the data analysis on user experience in Table 2, it shows that 60 respondents (49.3%) used generative AI once or several times a day, followed by 31 respondents (21.8%) who used generative AI once a day and 27 respondents (19.0%) have used generative AI once a week. Furthermore, the analysis on user experience demonstrated that 8 respondents (5.6%) use generative AI once a month, 2 respondents (2.8%) use generative AI once a month, and only 4 respondents (2.8%) never use generative AI. The data reveals that

almost three-quarters of the respondents have frequent usage and engage with generative AI every day or multiple times a day.

Reliability analysis was carried out in this study by calculating Cronbach's alpha values for each variable. A reliable measure should demonstrate both consistency and stability (Kaliani Sundram et al., 2016). According to Hair et al. (2011), a Cronbach's alpha value above 0.70 is considered acceptable. Hinton et al. (2004) also state that a value of 0.70 or higher shows good reliability, while slightly lower values are still acceptable. These results suggest that the items in the questionnaire reliably measure how respondents view the five factors.

Table 3 shows the Cronbach's alpha values for five variables: performance expectancy (0.934), effort expectancy (0.761), social influence (0.855), facilitating condition (0.836), and behavioral intention (0.934). Four variables, performance expectancy, social influence, facilitating condition, and behavioral intentions, show very strong reliability. Meanwhile, effort expectancy shows acceptable reliability. Table 3 presents the results for Cronbach's Alpha for the dependent variable for this study.

Table 3: Cronbach's Alpha

Variables	Cronbach's Alpha	Strength of Association
Performance Expectancy	.934	Very Strong
Effort Expectancy	.761	Strong
Social Influence	.855	Very Strong
Facilitating Condition	.836	Very Strong
Behavioral Intention	.934	Very Strong

Table 4: Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.772 ^a	.596	.585	.39935

a. Predictors: (Constant), Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Condition

b. Dependent Variable: Behavioral Intention

Table 5: ANOVA

Model	Sum of Squares	DF	Mean Square	F	Sig.
1 Regression	32.279	4	8.070	50.600	<.001 ^b
Residual	21.849	137	.159		
Total	54.129	141			

a. Predictors: (Constant), Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Condition

b. Dependent Variable: Behavioral Intention

Table 6: Coefficient Analysis

	Unstandardized Beta	Std. Error	Standardized Beta	t-value	p-value
Performance Expectancy	.257	.075	.272	3.435	<.001
Effort Expectancy	.258	.078	.266	3.315	.001
Social Influence	.081	.051	.101	1.571	.118
Facilitating Condition	.315	.063	.324	4.981	<.001

a. Dependent Variable: Behavioral Intention

In Table 4, the R Square value (0.596) in Model 1 indicates that approximately 59.6% of the variance in behavioral intention can be explained by the combined influence of performance expectancy, effort expectancy, social influence, and facilitating condition. The adjusted R Square (0.585) suggests that the model's predictive power remains consistent even after considering the number of predictors. The standard error of the estimate (0.39935) represents the average difference between the actual and predicted values, reflecting the accuracy

of the model in behavioral intention. In Table 5, the ANOVA table displays the sources of variance in the regression model. The regression model's sum of squares is 32.279, with 4 degrees of freedom, resulting in a mean square of 8.070. The F-value (50.600) is highly significant ($<.001$), indicating that the regression model as a whole significantly explains the variance in behavioral intention.

The coefficient analysis in Table 6 shows that performance expectancy has a significant positive effect on behavioral intention, with a p-value of less than 0.001. This means that when TVET educators believe that generative AI can help improve their performance, they are more likely to use it. The findings support those of Bhat et al. (2024), who found that educators see generative AI as helpful in teaching and improving their daily tasks. This highlights the importance of showing how AI can offer real benefits. As noted by Venkatesh et al. (2003), people are more willing to adopt new technologies when they believe it will make them more productive and help them make better decisions. Therefore, promoting the practical advantages of AI can help increase its acceptance among educators.

This study found that effort expectancy significantly influences the intention to use generative AI, with a p-value of less than 0.001. The high mean value suggests that users perceive technology as easy to learn and apply effectively in their teaching and learning processes. These findings are consistent with previous studies, which highlight that effort expectancy plays an important role in shaping educators' attitudes toward technology adoption (Anthony et al., 2023; Zhou et al., 2022). However, contrasting results by An et al. (2023) suggest that effort expectancy does not always have a significant effect on behavioral intention. Their study indicates that some educators may be concerned that the time and effort required to learn new technologies could increase their workload and negatively affect their efficiency. This highlights the need to ensure that AI tools are not only easy to use but also well-integrated into existing educational practices to reduce resistance.

Another factor examined in this study was social influence. The results showed that social influence had a p-value of 0.118, which is greater than the significance level of 0.05, indicating that it does not significantly affect behavioral intention. In the context of technology adoption, the views and behaviors of peers, superiors, and organizational leaders often shape an individual's willingness to adopt new technologies. However, the findings of this study suggest that respondents were more influenced by their perceptions of usefulness and ease of use rather than by external social pressure. This implies that social influence was not a strong predictor of the intention to use generative AI among the respondents. While the UTAUT model (Venkatesh et al., 2003) identifies social influence as a key factor in behavioral intention, its relevance can vary depending on the technology and the context in which it is applied. Supporting this, O'Dea (2023) noted that the effect of social influence depends on how individuals perceive their social environment and the specific conditions under which technology is introduced.

Facilitating conditions were found to have a significant positive effect on the behavioral intention to use generative AI, with a p-value of less than 0.001. Although the original UTAUT model (Venkatesh et al., 2003) does not include facilitating conditions as a direct predictor of behavioral intention, expecting its effect to become insignificant once performance and effort expectancy are accounted for, this study presents a different outcome. The findings indicate that supportive infrastructure and resources play a crucial role in influencing educators' willingness to adopt generative AI. Respondents expressed confidence in the availability of technical support, training, and other institutional resources needed to use AI effectively. This suggests that facilitating conditions are a key determinant in shaping behavioral intentions, especially in higher education settings. As highlighted by Alhwaiti (2023), the presence of reliable support systems increases user confidence and strengthens their intention to use emerging technologies like generative AI.

Moreover, the study found a relationship between the coefficient of performance expectancy (0.272), social influence (0.266), and facilitating conditions (0.324), meaning that an increase in all three variables increases behavioral intention in the use of generative AI; however, changes in social influence have no impact on behavioral intention.

In order to verify the moderating effect of use experience on the relationship between independent variables and dependent variables, it was examined using the PROCESS Macro model 1 for SPSS, which Hayes (2017) suggested. There were 5000 samples, a 95% confidence interval, and a bootstrap was utilized for verification.

Table 7: Summary of Moderation Analysis

MODEL	DV: BEHAVIORAL INTENTION					
	COEFF	SE	t	p	LLCI	ULCI
EE x Exp	.0915	.0462	1.9819	.0000	.0002	.1828
SI x Exp	.1472	.0591	2.4911	.0139	.0304	.2641
FC x Exp	.1464	.0533	-2.7459	.0068	0.0410	.2518

Table 7 shows that experience significantly moderates the relationship between effort expectancy and behavioral intention, with a coefficient of 0.0915 and a p-value of 0.000. The confidence interval (LLCI = 0.0002, ULCI = 0.1828) confirms this effect, as it does not include zero. This means that educators' experience with generative AI influences how strongly ease of use affects their intention to use it. Educators who use generative AI more frequently tend to find it easier to use and are more willing to adopt it. In contrast, those who rarely use technology may find it more difficult, reducing their intention to use it. These findings support earlier studies by Yi and Choi (2023), Izkair and Lakulu (2021), and Alkhwalid (2024), which also highlight the importance of experience in shaping attitudes toward new technologies. Providing more training and exposure could therefore improve acceptance among educators.

Meanwhile, the analysis shows that experience has a positive and significant effect on the relationship between social influence and the intention to use generative AI. The interaction coefficient is 0.1472, with a standard error of 0.0591 and a t-value of 2.4911. The p-value of 0.0139 ($p < 0.05$) confirms that the moderation effect is statistically significant. The confidence interval (LLCI = 0.0304, ULCI = 0.2641) does not include zero, showing the result is reliable. This means that educators with more experience are more influenced by social factors like peers or supervisors when deciding to use generative AI. Experienced users may follow existing practices and advice from colleagues, while less experienced users may be more open to adopting new tools based on social cues. This is supported by Wei et al. (2025) and Jaradat et al. (2020). However, Ab Jalil et al. (2022) found no such effect, suggesting that experience may not always change how social influence affects technology use. Overall, the impact of social influence can differ based on the user's level of experience.

Lastly, the analysis shows that experience moderates the relationship between facilitating conditions and behavioral intention to use generative AI, with a positive coefficient of 0.1464 and a significant p-value of 0.0068. The confidence interval (LLCI = 0.0410, ULCI = 0.2518) does not include zero, confirming the significance of this effect. Facilitating conditions refer to available support, resources, and infrastructure that help educators use AI effectively. However, their impact depends on the educator's level of experience. This study supports the UTAUT model (Venkatesh et al., 2003), which suggests that experience strengthens the influence of facilitating conditions. Experienced educators can adapt better and are less affected by the lack of support, while less experienced educators rely more on support systems to build confidence in using AI. Understanding this moderating role is important for institutions to support both experienced and inexperienced educators in adopting AI tools.

5. Managerial Implications and Recommendations

This study offers several practical insights for higher education leaders, especially within the Polytechnic and Community College (POLYCC) system in Malaysia. The results show that lecturers are more likely to use AI technology when they believe it can improve their teaching performance. Therefore, management should focus on showing how AI tools can support teaching and learning effectively. Emphasizing the benefits of AI in improving productivity and outcomes can encourage wider adoption among educators. The study also found that when AI tools are easy to use, lecturers are more willing to adopt them. This means that institutions should provide user-friendly systems and offer training to help lecturers become comfortable with AI. Training sessions, user manuals, and simple interfaces are important to reduce resistance to using new technology.

In addition, facilitating conditions such as technical support, proper infrastructure, and access to resources were found to significantly influence lecturers' intention to use AI. Institutions should ensure that educators have the tools, support, and guidance they need. Dedicated IT support and ongoing assistance can help overcome barriers to using AI.

Based on these findings, several recommendations are proposed. First, institutions should offer regular training and workshops tailored to the needs of lecturers at different skill levels. Second, they should set up a support team to provide help with AI tools. Third, sharing successful examples of AI use within the POLYCC system could inspire more lecturers to adopt the technology. Lastly, institutions should gather feedback from lecturers to monitor the impact of AI use and improve support over time.

Conclusion

The intention to adopt generative AI among educators in higher education institutions is primarily influenced by the ease of learning and the availability of skills required to use technology. The findings indicate that performance expectancy, effort expectancy, and facilitating conditions significantly and positively affect educators' behavioral intention to use generative AI. In contrast, social influence was found to have no significant impact; educators' decisions to adopt technology were not shaped by peers' or colleagues' encouragement.

This study highlights that educators are more inclined to adopt generative AI when they perceive it as beneficial, easy to use, and supported by adequate institutional infrastructure and resources. These insights offer valuable implications for developers and researchers seeking to enhance technology integration in education. Overall, the research contributes to the broader understanding of AI adoption within educational contexts, emphasizing the importance of perceived usefulness, usability, and support systems in influencing technology acceptance.

In addition, the study found that experience serves as a significant moderating factor in the relationship between effort expectancy, social influence, and facilitating conditions on the intention to use generative AI. Educators with more experience are typically more familiar with digital tools and are better equipped to adapt to new technologies, reducing their reliance on external guidance or peer influence (Venkatesh et al., 2003). This self-sufficiency allows them to navigate and adopt AI technologies with greater confidence. Conversely, less experienced educators may depend more on institutional support, social encouragement, and user-friendly system features to build their intention to use generative AI. These findings underscore the need for differentiated support strategies in technology implementation, tailored to the varying experience levels among educators.

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