Teacher's Acceptance and Intention to Use Artificial Intelligence Technology in Teaching and Learning Based on the UTAUT Model

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***Abstract*—The integration of Artificial Intelligence (AI) technology in teaching and learning is becoming increasingly prevalent, necessitating teacher preparedness for pedagogical reform. This study investigates the factors influencing secondary school teachers' acceptance of AI technology based on the Modified Integrated Theory of Acceptance and Use of Technology (UTAUT). Specifically, it examines the roles of Performance Expectation, Effort Expectation, Social Influence, and AI Anxiety in shaping behavioral intention, and explores the moderating effects of gender, age, and teaching experience. Data were collected through a structured questionnaire administered to 88 secondary school teachers in Kuala Lumpur, Malaysia. Statistical analyses, including one-way ANOVA and multiple linear regression using SPSS version 29, conducted to evaluate the data. The results reveal that Effort Expectation and AI Anxiety significantly influence behavioral intention, while Performance Expectation and Social Influence do not. Additionally, teaching experience positively moderates the relationship between predictor factors and behavioral intention, whereas gender and age have no moderating effect. These findings contribute to understanding the factors that promote AI technology acceptance among teachers and provide insights for strategies to enhance AI adoption in Malaysian education.**

***Keywords*—Artificial Intelligence (AI), Unified Theory of Technology Acceptance and Use of Technology model (UTAUT), behavioral intentions, in-service teacher**

I. Introduction

The rapid advancement of digital technologies in the era of Industry 4.0 (IR4) demands that education systems worldwide incorporate technology into Teaching and Learning (T&L). This integration is essential to prepare students for Society 5.0, an era where humans and machines collaborate through digital technologies such as Artificial Intelligence (AI), the Internet of Things (IoT), cloud computing, and Big Data. In alignment with the Fourth Sustainable Development Goal (SDG), the United Nations Educational, Scientific and Cultural Organization (UNESCO) has taken a strategic step by developing the AI Competency Framework for Teachers, an initiative designed to equip educators with the skills, knowledge, and ethical principles required to incorporate AI into their teaching practices [1].

In Malaysia, the Second Thrust in the Digital Education Policy (DEP) focuses on developing Digitally Competent Educators, aiming to produce knowledgeable, skilled and innovative digital teachers who can enhance the effectiveness of the T&L process [2]. AI plays a central role in this transformation, with its potential to revolutionize education by improving teaching practices, student engagement, and learning outcomes.

AI is generally defined as the ability of machines to think like humans. Huang, Rust, and Maksimovic [3] define AI as a set of computer programs and technologies that replicate the functions and intelligence of the human brain. AI systems replicate human characteristics such as learning, adapting to situations, synthesizing information, correcting errors, and processing complex tasks using data [4]. These capabilities enable AI to enhance educational experiences by introducing innovative technologies and teaching methods.

Several studies related to the benefits of using AI technology in education. For example, Elbanna and Armstrong [5] demonstrate that when effectively integrated into educational settings, AI tools such as ChatGPT can automate teachers' tasks and administrative duties, freeing up time and improving efficiency. This, in turn, allows teachers to concentrate more on tailored instruction, thereby enhancing teaching practices and fostering adaptive learning by tailoring learning experiences to individual needs. These technologies also support student achievement and accelerate cognitive development, equipping students to meet the challenges of the digital age [6, 7].

Furthermore, AI applications such as personalized learning systems, smart tutor programs, and automatic assessment tools have been shown to significantly improve learning outcomes and provide students with broader access to quality education globally [8]. By making education more interactive and dynamic, AI technologies can boost student motivation, create engaging learning environments, and help students develop the digital skills necessary for Society 5.0.

Despite these promising advantages, there remains some skepticism and resistance among teachers regarding the use of AI in the classroom. It is essential to explore teachers' perceptions of AI and the factors that encourage or hinder its adoption to fully realize the AI's potential in education.

II. Problem Statement

The education system is currently facing numerous challenges and unexpected constraints that require comprehensive reforms. Proactive measures must be taken to drive change in the country's educational landscape by leveraging AI technology to avoid falling behind on the global stage. Teachers play a pivotal role in this transformation, not only by facilitating learning but also by modeling adaptability and proactive engagement with new

technologies for their students. Lindner and Romeike [9] argue that teachers must be adequately prepared to address the challenges associated with the ineffective use of AI to ensure its successful integration into T&L.

The readiness of teachers to use technology is a critical factor, as they are the key drivers of digitization in education, particularly in the classroom. Several studies have found that technology has not been fully accepted, as many teachers maintain a negative attitude towards it and refuse to use it [10, 11]. Additionally, teachers' willingness to use technology is associated with a reluctance to accept and adapt to changes in modern technology [12]. This aligns with Munusamy and Jamaludin's [13] study, which found that many teachers reject digital-based teaching because they are not ready to accept changes.

Nowadays, the frequent use of technology devices such as computers and smartphones in daily life has led to significant changes in students' interests and their relationship with technology [14]. Therefore, new technology-based teaching materials that capture students' attention must be developed in line with current technological advancements. However, many teachers lack knowledge of AI and how it functions, which limits their ability to effectively integrate AI tools into their instructional practices. Studies by Chounta *et al*. [15], Celik [16], Chiu and Chai [17], and Hwang *et al*. [18] emphasize that teachers lack of understanding about AI prevents them from fully utilizing AI tools, thereby hindering its potential impact on improving T&L outcomes. Additionally, an international study by Drossel *et al*. [19] and IEA [20] discovered that only 41% of teachers reported having learned how to integrate digital technology into their teaching. This percentage is considered low, given that the world is in the IR4. This highlights the challenges in adopting AI in T&L, where teachers' perceptions of AI as a difficult tool to master contribute to their reluctance to use, reflecting the influence of effort expectancy on technology adoption in education.

Using new technology such as AI often evokes feelings of excitement, concern, and satisfaction. Studies have found that concerns among AI users, such as inconsistent data, potential biases, accuracy of information, lack of deep understanding, and ethical issues like data security and algorithm transparency, directly contribute to teachers' apprehension about integrating AI into their practices [6, 21, 22]. In the educational context, studies show that teachers are concerned that AI technology may reduce communication and interaction with students, replace their roles, and contribute to higher unemployment [23–25]. AlKanaan, Shin, Shin [26, 27] reveal that teachers often have limited awareness of AI technology, contributing to significant anxiety associated with its adoption.

Collectively, these issues not only heighten resistance in adopting AI but also highlight the need for targeted interventions to address the factors that significantly influence teachers' behavioral intentions toward AI adoption. Understanding and mitigating these factors is essential for enabling educators to effectively and ethically utilize AI technologies in their practices. By demonstrating adaptability to this new technology, teachers can inspire their students to engage with these tools critically and creatively.

III. Literature Review

A. Integrated Theory of Acceptance and Use of Technology

Fig. 1 shows an Integrated Theory of Technology Acceptance and Use (UTAUT) developed by Venkatesh *et al*. [28]. It is a theoretical model designed to explain and predict the factors that influence the acceptance and adoption of technology. UTAUT is an important concept because this model combines eight main theories reviewed and consolidated from the Theory of Causal Action (TRA), Technology Acceptance Model (TAM), Motivation Model (MM), Theory of Planned Behavior (TPB), Combined Acceptance Model Technology and Theory of Planned Behavior (C- TAM-TPB), Model of PC Usage (MPCU), Innovation Diffusion Theory (IDT), and Social Cognitive Theory (SCT). The model has been tested using a large real-world data set. UTAUT emphasizes four elements which are Performance Expectations, Effort Expectations, Social Influence and Facilitating Conditions which are driving factors for Behavioral Intention. This model proposes four independent variables namely gender, age, experience and willingness to use as moderators to the four main elements of behavioral intention and usage behavior.

The UTAUT model combines elements from eight existing models, enhancing its predictive power to 70%, which surpasses any previous technology acceptance model [28]. It is widely used to explore the acceptance factors of technological tools [29]. Additionally, the UTAUT model provides a comprehensive framework for understanding the adoption and use of technology [30] and has also been applied in studying the adoption of AI tools [31]. However, a review by Kittinger and Law [32] reveals that UTAUT is not widely used in the educational context, raising concerns about its generalizability and applicability in diverse environments. This concern is further supported by Or [33], which found a relatively low R^2 of 47.2%, and by Blut *et al*. [34], who argued that UTAUT is less robust than commonly assumed. Thus, these findings suggest that the model has limited explanatory power in educational settings. This calls for further investigation to explore how the UTAUT model can be adapted or refined to better explain technology adoption and usage in educational settings, particularly in the context of emerging technologies like AI tools.

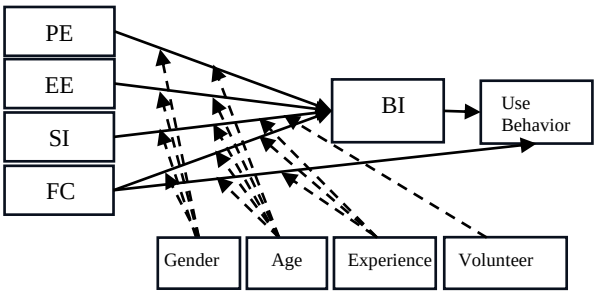

Fig. 1. UTAUT model [28].

While various empirical research has explored teachers' acceptance of AI technologies based on the UTAUT model across different regions, research on the Malaysian context remains significantly underexplored. Existing studies predominantly examine teachers' attitudes and behavioral

intentions in countries with diverse educational systems and AI adoption trends. This underscores a critical need to explore the applicability and effectiveness of the UTAUT model in understanding teachers' acceptance of AI technology within the unique educational and technological landscape of Malaysia, particularly in urban areas like Kuala Lumpur. Addressing these gaps will contribute to understanding the regional determinants of AI acceptance and inform policy development tailored to Malaysia's educational environment.

B. Conceptual Framework and Hypothesis development

AI utilization in education has experienced significant growth in recent years, sparking increased interest in studies on teachers' acceptance to adopt and use it using various theories of technology acceptance. Behavioral intention (BI) is considered a key predictor of actual behavior of technology use [28]. According to Ajzen [35], behavioral intention reflects an individual's readiness or willingness to engage in a particular behavior. The stronger the intention, the higher the likelihood of the behavior being performed, assuming the individual has the necessary control. In this context, teachers' intention to use AI technology reflects their readiness to accept it and the extent to which they integrate it into their practices.

Performance Expectancy (PE) is defined as the degree to which an individual believes that using the system will enhance their job performance [28]. This implies that users are more inclined to adopt and use the technology if they perceive it as useful for improving their performance. The research hypothesis is as below:

H1: PE directly, positively influences BI

Effort Expectancy (EE) refers to the degree of ease associated with using a system [28]. Three constructs from existing models capture this concept which are Perceived Ease of Use (TAM/TAM2), Complexity (MPCU), and Ease of Use (IDT). These constructs share substantial similarities in both their definitions and measurement scales, where previous research has highlighted these similarities [36, 37]. Users are more interested in using technologies that are easy to use [30, 38]. The research hypothesis is as below:

H2: EE directly, positively influences BI

Social Influence (SI) refers to the extent to which users perceive that people around them believe they should adopt the new system [28]. The research hypothesis is as below:

H3: SI directly, positively influences BI

AI Anxiety (AIA) refers to user's unique or unusual feelings of fear, discomfort, or apprehension when interacting with AI technologies, stemming from concerns about privacy breaches, bias, job replacement, learning concerns, existential risk, ethical violation, artificial consciousness, and lack of transparency [39]. AIA is also referred to "technophobia" [40]. Individuals with limited exposure to AI or insufficient support, less experience and lack of knowledge about AI may experience increased anxiety, which can further intensify resistance to AI integration [41, 42]. Given the potential of AIA to hinder AI adoption, particularly in educational contexts where teachers' reluctance could limit its benefits, it is crucial to include AIA as a factor of acceptance to better understand and address this barrier. A relationship between AIA and BI was observed [43] but it remains unclear whether and how AIA directly influences BI. This highlights another gap in the literature, emphasizing the need for further research to explore the direct effects of AIA on the adoption of AI. Therefore, this study proposed this hypothesis:

H4: AIA directly, negatively influences BI

For the moderator of gender, age and teaching experience, the researcher tested the following hypotheses:

H5: Gender moderates the influence of PE, EE, SI and AIA on BI.

H6: Age moderates the influence of PE, EE, SI and AIA on BI.

H7: Teaching experience moderates the influence of PE, EE, SI and AIA on BI.

Fig. 2 illustrates the conceptual framework of this study is designed to address the following research questions:

1) Is there a significant effect of the factors PE, EE, SI and AIA on teachers' BI to use AI-based technology in T&L?
2) Is there a moderating effect based on the demographic factors of gender, age and teaching experience on teachers' BI to use AI- based technology in T&L?

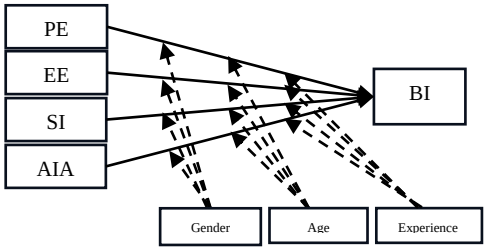

Fig. 2. Conceptual framework.

IV. METHODOLOGY

This study employs a quantitative approach utilizing questionnaire surveys. Survey research is often used to assess attitudes, characteristics, trends, and perceptions [44]. Surveys can help minimize bias as they allow respondents to answer questions without the researcher's presence, thereby preserving anonymity.

A. Population and Sampling

The study population is secondary school teachers from various disciplines in Bangsar and Pudu districts under the supervision of the Kuala Lumpur Federal Territory Education Department (JPWPKL). As of June 14, 2024, data from the JPWPKL Education Basic Information portal indicates that the population includes 8649 teachers [45]. The sample size for this study was determined based on Cohen's (1992) sample size determination table [46, 47]. The researcher considers the significance level of $p < 0.05$ with a power of .80 and a medium effect size, for a multiple regression analysis study using five independent variables, the proposed sample size is 84 teachers. The probability sampling procedure is carried out using a two-tier cluster sampling method considering the large number of the population and the list of subjects could not be obtained. The researcher selects 10 schools from all schools using simple random sampling, then 10 teachers from each school using random sampling are selected. The research instrument was given in the form of Google Forms to the sample.

B. Instrument

The instrument used was an open-ended questionnaire developed based on the UTAUT Model referencing to the scale of Venkatesh *et al*. [28] and other related researchers. The questionnaire is divided into three parts. The first part is the teacher's demographic information which contains 5 items. The second part is a survey of teachers' readiness to use AI technology containing 4 items. The third part is a survey of various factors that influence teachers to use AI technology based on the elements in the UTAUT model. There are 4 items for the PE factor, 4 items for the EE factor, 4 items for the SI factor, 4 items for the AIA factor and the last 3 items for the dependent variable which is BI. The total number of questionnaire items is 24 items. The five-point Likert scale is used, which is a scale of 1 to 5 representing "strongly disagree", "disagree", "neutral", "agree" and "strongly agree" to evaluate the level of response.

V. Result

The findings of the study were analyzed using the Statistical Package for the Social Sciences (SPSS) software version 29. Descriptive analysis techniques and multiple linear regression analysis were used.

A. Demography

A total of 88 respondents completed the questionnaire. Table 1 shows the number of male teachers is 23 (26.1%), and the number of female teachers is 65 (73.9%). Most respondents are between 31-40 years old (52.3%) and the fewest are over 50 years old (4.5%). 81.8% of all respondents are Malay while the rest are Chinese (13.6%) and Indian (4.5%). The educational background of the majority of respondents has a bachelor's degree (65.9%), a Master's (32.9%) and a Doctor of Philosophy (1.1%). In terms of teaching experience, there are 17 teachers (19.3%) with less than 10 years of teaching experience, 50 teachers (56.8%) between 10 and 20 years of experience, while the remaining 21 teachers (23.8%) have 20 years of experience and up.

Table 1. Demography

Demography	Category	Frequency	%
Gender	Male	23	26.1
	Female	65	73.9
Age (years)	< 30	6	6.8
	31–40	46	52.3
	41–50	32	36.4
	51–60	4	4.5
Race	Malay	72	81.8
	Chinese	12	13.6
	Indian	4	4.5
	Others	-	-
Educational background	Bachelor	58	65.9
	Master	29	32.9
	Phd	1	1.1
Teaching experience (years)	0-5	4	4.5
	5–10	13	14.8
	10–15	24	27.3
	15–20	26	29.5
	20–25	20	22.7
	25–30	1	1.1

B. Item Reliability and Validity

Table 2 shows the results of the Cronbach's Alpha (α) reliability test for all 5 constructs including all the number of items for each independent variable. The analysis found that the α values for the PE, EE, SI, AIA and BI are at a high level of reliability at $\alpha > 0.8$. Based on the Cronbach's Alpha scale [48], the reliability level of the study instrument is at a high and very high level. Thus, all constructs for each variable can be trusted for further analysis. Table 3 shows statistical value of Kaiser Meyer Olkin (KMO) test and Bartlett's Test of Sphericity. KMO=0.828, $\chi 2 = 1209.106$ ($p < 0.001$), indicates that the correlation between the variables is significant, showing that the questionnaire items have good validity. Thus, factor analysis could be conducted.

Table 2. Cronbach's Alpha (α)

Variables	No. of Item	Cronbach's Alpha (α)
PE	4	0.939
EE	4	0.938
SI	4	0.847
RA	4	0.923
BI	3	0.941
Total	19	0.843

Table 3. KMO and Bartlett's test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		**0.828**
Bartlett's Test of Sphericity	Approx. Chi-Square	2267.246
	df	253
	Sig.	<.001

C. Descriptive Statistics

Table 4 shows diverse perceptions among respondents. PE has the highest mean ($M = 4.3750$, $SD = 0.65324$), indicating very high expectations of performance benefits from the respondents, with a relatively low standard deviation. EE has a high mean score ($M = 4.0909$, $SD = 0.75732$) reveals that respondents perceive the system as relatively easy to use. SI has a high mean ($M = 3.8097$, $SD = 0.80765$), implying that social influence is perceived positively by respondents. AIA records the lowest mean score ($M = 2.3523$, $SD = 0.84981$), which indicates a generally low level of anxiety about AI among participants. The standard deviation of all variables (PE, EE, SI and AIA) is less than 1.0, indicating that the scores are densely scattered around the mean value, suggesting low variability and consistent responses among participants. However, AIA shows the highest variation, reflecting more variation than other variables. It indicates that some participants expressing more anxiety than others.

Table 4. Descriptive statistics

Variables	Mean	Std. Deviation	Level
PE	4.3750	0.65324	Very high
EE	4.0909	0.75732	High
SI	3.8097	0.80765	High
AIA	2.3523	0.84981	Low
BI	4.0417	0.75609	High

D. Regression Model

The value of R squared (R^2) or known as the coefficient of determination measures how far the dependent variable can be explained by the independent variable in the regression model. It measures the proportion of the total variation in the dependent variable that is explained by independent variable. Based on Table 5, $R^2 = 0.605$ means 60.5% variation for the

BI factor can be explained by PE, EE, SI and AIA factors, while 39.5% is explained by other factors that were not studied. The entire regression model is significant, [$F(4, 83) = 31.758$, $p < 0.001$, $R^2 = 0.605$], as shown in Table 6. According to Cohen's effect size guidelines, $f^2 = R^2/(1 - R^2) = 1.53$, indicating that the overall effect size of the model is very strong [49]. While this value exceeds Cohen's thresholds for individual predictors, it highlights the robustness of the combined predictors in explaining behavioral intention, making it a significant finding in quantitative research.

Table 5. Model summary

Model	R	R^2	Adjusted R^2	Std. Error of the Estimate
1	0.778[a]	0.605	0.586	0.48662

Table 6. ANOVA

	Sum of Squares	df	Mean square	F	Sig
Regression	30.081	4	7.520		
Residual	19.655	83	0.237	31.758	< 0.001
Total	49.736	87			

Table 7 shows only two predictive factors that have a significant impact on BI, which is EE ($\beta = 0.582$, $t = 4.701$, $p < 0.001$) and AIA ($\beta = -0.267$, $t = -3.701$, $p < 0.001$). However, the other two factors, PE ($\beta = 0.52$, $t = 0.370$, $p = 0.712$) and SI ($\beta = -0.023$, $t = -0.260$, $p = 0.795$), did not have a significant effect on BI. As a result, H2 and H4 are accepted, while H1 and H3 are rejected.

Table 7. Coefficients

Model		Unstandardized Coefficients		t	Sig
		β	Std. Error		
1	(Constant)	2.151	0.528	4.077	<.001
	PE	0.052	0.141	0.370	0.712
	EE	0.582	0.124	4.701	<.001
	SI	−0.023	0.088	−0.260	0.795
	AIA	−0.267	0.072	−3.701	<.001

E. Moderating Effects of Gender, Age and Teaching Experience

Table 8 shows the results from the t-test for the difference between males ($M = 3.84$, $SD = 0.78$) and females ($M = 4.11$, $SD = 0.74$) on BI. The results show that there is no significant difference in BI to use AI technology based on gender $t(86) = -1.495$, $p = 0.139$. H5 is rejected.

Table 8. Gender differences on BI

Gender	N	Mean	Std. Deviation	t	Sig
Male	23	3.8406	0.78412	−1.495	0.139
Female	65	4.1128	0.73899		

ANOVA results for differences in behavioral intention according to age group are presented in Table 9. There is no significant difference in BI to use AI technology based on age group $F(3,84) = 1.187$, $p = 0.320$. H6 is rejected.

Table 10 shows the results of one-way ANOVA analysis of the variance of behavioral intention differences according to teaching experience. There is a significant difference in BI to use AI technology based on teaching experience $F(5,82) = 2.957$, $p < 0.05$. H7 is supported.

Table 9. Age difference on BI

Age (years)	N	Mean	Std. deviation	F	Sig
20–30	6	4.2778	0.57413	1.187	0.320
31–40	46	4.0797	0.74099		
41–50	32	3.8854	0.81037		
51–60	4	4.5000	0.57735		

Table 10. Differences in teaching experience against BI

Teaching Experience (years)	N	Mean	Std. deviation	F	Sig
0–5	4	4.6667	0.47140	2.957	0.017
5–10	13	4.2308	0.61440		
10–15	24	4.1389	0.73502		
15–20	26	4.0256	0.67279		
20–25	20	3.8000	0.83351		
25–30	1	2.0000			

VI. Discussion

This study addresses two research questions. First, it aims to identify the factors influencing teachers' acceptance of AI technology based on modified UTAUT model, along with one external variable. Second, it seeks to determine whether gender, age, and teaching experience significantly affect the adoption of AI technology. This study has confirmed the predictors of behavioral intention for seven research hypotheses.

An intriguing and unexpected outcome of this study was the rejection of the hypothesis that PE has a direct and positive influence on BI. Although PE is commonly regarded as the most potent predictor of BI in UTAUT as supported by previous research [28, 32, 33, 50] and is significant in similar context of studies [51–54], our findings are contrary. This suggests that the perceived benefits of using technology did not significantly impact teachers' intention to adopt it. Such findings pose a challenge to the foundational assumption of the UTAUT model, which posits that users are more likely to adopt a technology if they believe it will improve their performance. However, these findings support the study by Cojean and Martin [55], which found that PE influenced the acceptance of AI among primary school teachers but had no effect on secondary school teachers. This study also aligns with Omar, Ismail and Kasim [56]; Mtebe, Mbwilo and Kissaka [57]; and Nandwani and Khan [58]. Possible explanation for this rejection could be contextual factors, where teachers' environment has less emphasis on the performance improvements associated with AI technology use. Teachers may perceive that using AI in T&L does not provide any significant advantage or improvement to their job. This could be linked to a lack of knowledge and awareness about AI technology, whereby studies have found that teachers in Malaysia generally have an average level of knowledge about AI [59–61]. Lack of sufficient knowledge about how to use technology effectively may prevent teachers from recognizing its potential benefits or understanding how it could enhance their performance, thereby reducing the influence of PE on BI to use AI technologies. In addition, it is also possible that other mediating or moderating factors are influencing the variation

in predictions, which explains why PE's impact on BI is weaker or less consistent in this study context.

This study reveals that EE has a positive and significant effect on BI, aligning with the UTAUT and TAM models, which emphasize EE as a strong predictor of technology acceptance [28, 36]. These findings support the research by Zhang *et al*. [10] and Bhat *et al*. [62], indicating that teachers are more likely to adopt AI technology when they perceive it as easy to use and require minimal effort. However, these results contradict early research conclusions [49, 50, 51, 63] where EE did not significantly impact AI adoption. These discrepancies may arise from differences in context, sample, or other moderating factors influencing the relationship between EE and BI.

Third hypothesis suggesting that SI would predict AI acceptance, was not supported. The results showing that social support from colleagues and administrators has no effect on the acceptance of teachers to use AI technology in T&L. This finding aligns with Ayanwale *et al*. [53], Savalli [64] and Cojean and Martin [54], who also found SI irrelevant in secondary school teachers' adoption of AI. However, it contrasts with review by Kittinger and Law [32] which identified SI as a key factor in AI adoption. The findings implies that teachers may be less influenced by social support when considering the adoption of AI technologies. One potential reason is the introduction of extension variables in the model might explain the diminished impact of SI observed in our findings, as it could potentially weaken or even reverse SI's effect [34]. Additionally, while teachers display high interest in using AI technologies like ChatGPT [58], their hesitance influenced by negative social perceptions underscores the complex dynamics at play [61].

Further, AIA has a significant negative effect on BI, suggesting that higher levels of anxiety or fear related to AI technology reduce teachers' willingness to adopt and use AI in T&L. This aligns with previous research indicating that anxiety around technology can hinder its acceptance and use [41, 42]. Specifically, teachers who experience higher levels of AIA may hesitate to incorporate AI tools into their educational practices. The more anxious or skeptical they are about AI, the less likely they are to intend to use or accept AI technologies. Although some research has downplayed the impact of anxiety on AI technology adoption [10, 53], our findings underscore the necessity of addressing risk concerns associated with AI technology, which inhibit teachers' adoption of AI in T&L.

Regarding the findings on moderator effects, this study found that teaching experience has a positive moderating effect on BI to use AI technology. This suggests that more experienced teachers might be more confident and open to using new technology than less experienced teachers. This finding aligns with the results reported by Zhang and Wareewanich [50] who found that teaching experience acted as important moderators in the adoption of generative AI. In contrast, gender and age do not show a moderating effect, which is inconsistent with the assumption of the original UTAUT model [28]. The inconsistency may be partially explained by the gender and age composition of the sample. The relatively lower proportion of male respondents (26%) compared to female respondents (74%) could potentially limit the ability to detect gender-based differences in moderating effects. This finding aligns with White Baker *et al*. [65], who found that gender and age do not moderate the TPB constructs in relation to the BI to use technology, likely due to the larger proportion of males in the study. When one group predominates in the sample, it may overshadow or underrepresent the attitudes and experiences of the less-represented group, leading to less pronounced moderating effects [66].

Furthermore, the relative homogeneity of technology acceptance attitudes within the specific demographic groups studied may also explain the diminishing role of age and gender as moderating factors [67]. Malaysia's ranking of 24th in Government AI Readiness Index 2024 [68] and 22nd in the training and education component of the 2024 World Digital Competitiveness Index [69] reflect the significant strides made in enhancing digital skills and integrating technology. These advancements indicate that government initiatives in the education sector have become more widespread with consistent exposure and training, impacting teachers across all age groups and genders. Consequently, it is plausible that the impact of gender and age on AI acceptance in this study has been reduced as teachers are equally capable of engaging with AI technology in T&L.

VII. Conclusion

This study explores the factors influencing secondary school teachers' acceptance of AI technology in T&L, employing the modified UTAUT model. The findings reveal that Effort Expectancy and AI Anxiety significantly impact teachers' behavioral intention to adopt AI, with Effort Expectancy having a positive effect and AI Anxiety exerting a negative influence. Interestingly, Performance Expectancy and Social Influence were not significant predictors, which challenges the prevailing assumptions of the UTAUT regarding the universal applicability of these factors. Teaching experience was found to be a positive moderator, suggesting that experienced teachers are more confident and open to adopting new technologies. In contrast, gender and age did not demonstrate moderating effects, potentially due to the relative homogeneity of the sample and evolving norms surrounding technology use across demographics.

This study underscores the necessity to reevaluate the UTAUT model's predictive effectiveness across various cultural and educational landscapes. It also provides actionable insights for policymakers, the education institutions, and technology developers to craft targeted interventions that overcome barriers to AI integration in T&L. There is a critical need for educational policies and professional development programmes tailored to address the diverse backgrounds and experiences of teachers.

Educational stakeholders should prioritize simplifying AI tools and providing user-friendly interfaces tailored to teachers' needs to leverage the significance of Effort Expectancy. Schools and education departments can organize hands-on training sessions to enhance teachers' confidence in using AI and demonstrate its ease of integration into teaching practices. Offering step-by-step guides, video tutorials, and access to technical support can further reduce perceived complexity. Additionally,

incorporating AI tools gradually into existing workflows allows teachers to adapt comfortably, fostering a positive perception of ease of use. These strategies ensure that teachers view AI technologies as accessible and manageable, encouraging their adoption in educational practices.

Education institutions should plan a programme to focus on reducing teachers' anxiety about AI and emphasize on AI ethics and literacy to encourage AI adoption. This will provide teachers with a strong foundation in the fundamental concepts and ethical principles of AI, such as transparency and responsibility. Introducing the concept of "AI for All" can further inspire teachers to utilize AI for both personal and work benefits. A practical and comprehensive approach that includes impactful training and awareness initiatives will create a supportive environment that AI technologies are perceived as beneficial and secure. Thus, it enhances teachers' knowledge and awareness of how AI can improve teaching and learning.

This research not only sheds light on the specific conditions under which AI technology is accepted by teachers but also prompts a broader reflection on the methodologies and theories used to study technology adoption in education. There is a need for theories that can more accurately reflect the realities of diverse educational environments and that can guide the development of more effective, inclusive, and adaptive educational technologies.

However, there are several limitations to consider when interpreting the findings of this study, which affect its generalizability. First, the geographic context and demographic composition of the sample is a key limitation. The sample consisted of 88 secondary school teachers from the Federal Territory of Kuala Lumpur, Malaysia, specifically in an urban area. These findings may not be fully applicable to rural settings or broader populations, particularly in countries or regions with differing educational policies, infrastructures, or cultural norms. Future research should involve larger and more diverse populations with a more balanced gender distribution to better capture the nuanced influences of demographic factors. Second, the data for this study was collected through a quantitative approach on a one-off basis. Incorporating qualitative data in future research could offer more in-depth insights into the predictors influencing teachers' acceptance of AI. Adopting a mixed-methods approach combining both quantitative and qualitative data would offer a more holistic and nuanced understanding of the study context. Despite these limitations, this study makes valuable contributions to the literature on technology adoption, particularly in the context of secondary education in Malaysia.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

S. Muhamed conducted the research, wrote the paper, and analyzed the data, I. F. Kamsin, reviewed and finalized the paper. Both authors had approved of the final version.

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