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Factors Affecting the Adoption of AI-Based Applications in Higher Education: An Analysis of Teachers' Perspectives Using Structural Equation Modeling

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ABSTRACT: Owing to the rapid advancements in artificial intelligence (AI) technologies, there has been increasing concern about how to promote the use of AI technologies in school settings to enhance students' learning performance. Teachers' intention to adopt AI tools in their classes plays a crucial role in this regard. Therefore, it is important to explore factors affecting teachers' intention to incorporate AI technologies or applications into course designs in higher education. In this study, a structural equation modeling approach was employed to investigate teachers' continuance intention to teach with AI. In the proposed model, 10 hypotheses regarding anxiety (AN), self-efficacy (SE), attitude towards AI (ATU), perceived ease of use (PEU) and perceived usefulness (PU) were tested, and this study explored how these factors worked together to influence teachers' continuance intention. A total of 311 teachers in higher education participated in the study. Based on the SEM analytical results and the research model, the five endogenous constructs of PU, PEU, SN, and ATU explained 70.4% of the changes in BI. In this model, SN and PEU were the determining factors of BI. The total effect of ATU was 0.793, followed by SE, with a total effect of 0.554. As a result, the intentions of teachers to learn to use AI-based applications in their teaching can be predicted by ATU, SE, PEU, PU and AN. Among them, teachers' SE positively influenced teachers' PEU and ATU towards adopting AI-based applications, and also influenced PU through PEU. In addition, the relationship between teachers' SE and AN was negatively correlated, which indicated that enhancing teachers' SE could reduce their AN towards using AI-based applications in their teaching. Accordingly, implications and suggestions for researchers and school teachers are provided.

Keywords: Artificial intelligence, Higher education, Anxiety, Self-efficacy, Technology acceptance model

1. Introduction

With their development, technologies have had substantial influences on teaching management, teaching innovation and the analysis of learning behavior (Nelson et al., 2019). In particular, the development of speech recognition, natural language recognition and deep learning has fostered educators' attention to artificial intelligence (AI) technologies. AI has been described as computers being used to mimic human minds so as to perform cognitive tasks (e.g., thinking, learning, problem solving) (Hwang, 2003; Nilsson, 2014). AI technologies can analyze learners' learning process, provide adaptive learning resources, and provide evaluation and suggestions based on learners' performance, which can serve as a learning diagnostic tool (Colchester et al., 2017; Hwang et al., 2011; Timms, 2016).

AI technologies have been gradually changing the role of teachers in learning activities; teachers can select appropriate AI teaching tools to monitor learners' learning processes and offer them personalized and timely assistance (Edwards et al., 2018). Researchers have indicated that developing a virtual laboratory, an intelligence teaching platform or an intelligence learning tool based on AI technologies can support diverse learning approaches, provide learners with personalized guidance, learning prompts and feedback, and assist learners in developing higher order thinking abilities as well (Hwang, 2014; Lin et al., 2018; McArthur et al., 2005). Moreover, with the development of communication and computing technologies, Artificial Intelligence in Education (AIEd) has become an important issue in education (Hwang et al., 2020c; Chen et al., 2020b).

From the perspective of precision education, AI technologies could analyze and predict learners' academic achievement, and intelligent tutoring systems (ITSs) could provide personalized instruction or support to students by understanding learners' learning status and behavior, diagnosing students' learning status and giving feedback automatically, to assist teachers with instructional assessment (Chen et al., 2020a; Hwang et al., 2020c; Hwang et al., 2014; Lin al., 2021). AIEd is a highly technology-dependent and cross-disciplinary field, and while AI technologies are being integrated into education, their use in teaching remains a challenge; for example, researchers might fail to effectively implement AIEd applications and activities without understanding the role of

AI in education and the functions of AI technologies (Hwang et al., 2020a). In addition, teachers who understand the functions and attributes of AI technologies can adopt suitable AI applications in their classrooms to promote students' motivation, engagement, or learning achievement (Chen et al., 2020a; Hwang et al., 2020c; Hwang et al., 2021). In this situation, it is crucial to understand teachers' standpoints on employing AI in teaching (e.g., their attitude towards AI and intention to use it) because teachers' acceptance or rejection will affect the application of AI to the teaching process (Popenici & Kerr, 2017).

Teacher acceptance has been proven to be an essential element in the process of educational innovation (Chen et al., 2009; Sánchez-Prieto et al., 2017). For instance, some studies have explored teachers' acceptance of adopting mobile technologies or digital technologies in teaching activities, while others have examined teachers' self-efficacy, perceptions (including usefulness and ease of use), feelings and attitudes towards adopting technologies (Nikou & Economides, 2017; Sánchez-Prieto et al., 2016; Scherer et al., 2019; Teo et al., 2008). Researchers have indicated that teachers' attitudes towards the adoption of AI technologies determine whether they will be used to support teaching activities, and the degree to which the technologies and actual teaching practice are integrated (Becker et al., 2017; Edwards et al., 2018; Wang & Wang, 2009).

In the field of education research, the Technology Acceptance Model (TAM) is most commonly used to explain teachers' attitudes and behavioral intention to use novel technologies to support teaching activities (Al-Emran et al., 2018; Scherer et al., 2019; Teo, 2019). On the other hand, researchers have pointed out the extra work that teachers need to do to prepare the new materials or to start teaching activities for the new technology/system, the time it takes to perform the necessary training, and the anxiety that comes from not being able to smoothly use the new technology/equipment (Sánchez-Prieto et al., 2017). Studies have also specified that reducing teachers' anxiety about the adoption of technologies and promoting teachers to effectively apply technologies in class can strengthen their confidence in adopting technologies (Clark-Gordon et al., 2019; Lim & Khine, 2006; Sánchez-Prieto et al., 2017). Sánchez-Prieto et al. (2017) also reported that teachers' beliefs about their ability to perform their tasks and achieve their goals were stronger in facilitating attitudes and willingness to adopt technology in teaching. Teachers' adoption of technology/systems in their teaching is a complex and multi-directional issue, and if teachers lack sufficient motivation and intention to employ technology/systems, then the unused technology/systems will eventually become useless (Bai et al., 2019; Hwang et al., 2020a; Teo, 2019; Sánchez-Prieto et al., 2016; Wang & Wang, 2009). Therefore, the present study aimed to investigate teachers' attitudes towards and intentions to adopt AI-based applications in their teaching, and based on TAM with the extension of two constructs: anxiety and self-efficacy, to explore teachers' perspectives, attitudes and behavioral intentions to integrate AI-based applications into teaching. The findings could be a good reference for those instructors and policymakers in schools or institutes.

2. Literature review and model development

2.1. Artificial intelligence in education (AIEd)

Due to the advancements in computer technology, the development of computer systems that are closer to human reasoning, decision-making and problem-solving capabilities has also received increasing attention. AI aims for human-level intelligence; researchers define AI as a computer-controlled device which has a human-like manner and is able to perform tasks such as learning, reasoning and self-correction (Chen et al., 2020b; Hwang, 2003; Nilsson, 2014; Shi & Zheng, 2006). Also, AI is referred to as Machine Intelligence or Computational Intelligence. In the past decades, researchers have attempted to apply AI to different fields such as playing chess, speech recognition, writing poetry, Intelligent Personal Assistants (IPAs) and diagnosing diseases (Aibinu et al., 2012; Hwang et al., 2020c; Russell & Norvig, 2003).

AIEd has become one of the current emerging fields of novel educational technology. AI technologies overcome the limitations of space and time; with the portability of mobile devices, learners can read the materials, practice and collect information at any time. In the meantime, AI learning systems can provide learning guidance and required auxiliary materials based on the learners' environment (Hung et al., 2014; Liu et al., 2019). Zawacki-Richter et al. (2019) reviewed the papers relevant to AIEd published from 2007 to 2018, and found that the main application fields of AIEd were profiling and prediction, assessment and evaluation, adaptive systems and personalization, and ITSs. For instance, ITSs can provide personalized learning interfaces and materials by analyzing students' personal learning characteristics and status (Chen et al., 2020a). Also, it can select teaching strategies and approaches based on students' current status and provide students with adequate assistance and timely guidance in order to facilitate the effectiveness of learning (Huang & Chen, 2016; Hwang, 2003; Van Seters et al., 2012). Moreover, in adaptive and intelligent web-based educational systems, taking into account both the affective and cognitive status of individual learners, the adaptive learning model could improve learners' learning outcomes and assist low achievers in successfully completing learning tasks (Hwang et al., 2020b). Some scholars have also tried to build user learning models by targeting large-scale data sources in learning systems and educational environments with big data analysis (e.g., Rau et al., 2017).

The interaction data analyzed by AIEd to support learners' learning processes can serve as a mentor for every learner. Besides, AIEd can provide insights into students' learning progress so that teachers can actively offer support and guidance when students are in need (Hwang et al., 2020c; Hwang et al., 2021; Woolf et al., 2013). However, researchers have indicated that applying technologies in educational environments should consider learning content, pedagogy and the environment created by the students, teachers and technology (Hsieh & Tsai, 2017; Oblinger, 2012). Some researchers have also found that teachers' acceptance level of AI technologies will influence the integration of AI and teaching activities, which is also one of the challenges of AIEd (Ifinedo et al., 2020; Popenici & Kerr, 2017; Teo et al., 2008; Zawacki-Richter et al., 2019). As a result, understanding teachers' acceptance of AI and relevant influencing factors is a current important research issue.

2.2. Technology acceptance model (TAM)

The TAM was first proposed by Davis et al. (1989) to explore users' acceptance of technologies. TAM emphasizes the users' intention to use or their actual use of technologies (Al-Emran et al., 2018; Bai et al., 2019; Legris et al., 2003). When users believe that technologies are helpful, they will then adopt those technologies and have a positive attitude towards them. On the other hand, when users think that specific technologies are easy to use and can help them complete tasks more effectively, they generally have stronger willingness to adopt them (Davis, 1989; Sánchez-Prieto et al., 2017; Teo, 2019; Wang & Wang, 2009). In other words, if the technologies are not easy to use, users will maintain the status quo or choose other options even if the technology is helpful (Teo, 2019). Studies have also indicated the importance of teachers' attitudes towards the integration of new technologies (including mobile learning platforms, virtual environments) into teaching for their adoption behavior (Dávideková et al., 2017; Hsieh & Tsai, 2017; Ifinedo et al., 2020).

Several studies have adopted TAM to explain teachers' intentions and behavior of employing new technologies in their teaching activities (Al-Emran et al., 2018; Scherer et al., 2019; Teo, 2019). For instance, teachers' self-efficacy for new technologies will influence the positive evaluation of their perceptions (e.g., perceived usefulness and ease of use), which will then affect their attitude and behavior of using new technologies when teaching. Other studies have specified that teachers' positive or negative perceptions when adopting new technologies will also affect their attitude and behavior of adoption (Bai et al., 2019; Sánchez-Prieto et al., 2017). Besides, researchers have specified that after users employ the technology, as they become familiar with the technology, their concern about "ease of use" becomes less, which could influence users' perceptions of its ease of use as well as their attitude toward their adoption of the technology (Lin, 2011; Teo, 2019; Wang & Wang, 2009). With the development of technologies, constructing smart learning environments (SLEs) to support teaching and learning has become a trend and a crucial goal for educational practitioners. This highlights that teachers play an important role in the process of applying AI technologies in teaching and learning activities (Kinshuk et al., 2016; Hwang, 2014). As a result, based on TAM, the present study examined teachers' perspectives, attitude and behavioral intention to integrate AI technologies into teaching.

2.3. Self-efficacy (SE)

In the context of information technology, SE is often defined as one's SE of using that technology, which refers to one's own judgement about one's ability to complete a specific task by using technology (Compeau & Higgins, 1995; Teo, 2019). Some studies have indicated that SE not only directly influences users' perceived usefulness of the technology, but also affects their attitudes towards the adoption of the technology (Motaghian et al., 2013; Teo & Zhou, 2014; Yeşilyurt et al., 2016). Teachers' SE is defined as their belief in their own capabilities. This can facilitate students' learning and is also the key point of integrating technology into teaching (van Dinther et al., 2013). Researchers have found that teachers with higher SE were more likely to successfully integrate teaching into their instruction (Bai et al., 2019). For example, in the flipped teaching activities in class, university instructors' SE influences their attitude towards using technology (Lai et al., 2018). The abovementioned studies indicated that teachers' SE in technologies is the belief in applying technologies when teaching, which has effects on their ease of use and attitude (Teo & Zhou, 2014; Yeşilyurt et al., 2016).

2.4. Anxiety (AN)

AN is generated due to users' anxious and nervous feelings about novel technologies. Studies have specified that users' negative feelings caused by the adoption of new technologies, such as AN, might negatively influence their attitude and SE (Agudo-Peregrina et al., 2014; Cazan et al., 2016). The relationship between AN and users' adoption of new technologies has been verified, for example, anxiety has a negative effect on teachers' and students' attitude towards the adoption of mobile technologies (MacCallum & Jeffrey, 2014). Studies have revealed that university teachers' attitudes towards adopting technologies when teaching are influenced by their AN. That is to say, teachers' feelings (positive or negative) about integrating technologies into teaching affects their adoption attitude (Clark-Gordon et al., 2019; Park et al., 2019).

2.5. Research model and hypotheses

Since Davis proposed the TAM model, it has been extensively verified and applied by the industry and academia in numerous relevant studies. Especially for teachers who integrate technologies into teaching, it also has its predictive power (Ifenthaler & Schweinbenz, 2013; Sánchez-Prieto et al., 2017; Teo, 2019; Ursavaş et al., 2019; Wang & Wang, 2009). Based on TAM, the present study adopted the six factors of AN, SE, PU, PEU, ATU and BI to explore teachers' perspectives, attitude and behavioral intention to employ AI-based applications to support their teaching. The research model is shown in Figure 1.

According to the literature, the university teachers' PEU, PU, and attitudes towards adopting technologies for teaching could have effects on their BI; their PEU and PU also influence their attitudes toward adopting AI applications in teaching activities (Kao & Tsai, 2009; Teo, 2019; Wang & Wang, 2009). Also, university teachers' PEU and PU of adopting technologies could directly or indirectly affect their BI. Researchers have also shown that teachers' PEU of using AI applications could affect perceptions of PU, ATU, and BI (Kao & Tsai, 2009; Wang & Wang, 2009). Therefore, based on TAM, the present study investigated university teachers' acceptance of AI technologies and relevant influencing factors. The research hypotheses of the present study are as follows:
H1: PU has a significant positive effect on ATU.
H2: PEU has a significant positive effect on PU.
H3: PEU has a significant positive effect on ATU.
H8: PU has a significant positive effect on BI.
H9: ATU has a significant positive effect on BI.
H10: PEU has a significant positive effect on BI.

In this study, SE refers to the measure or extent of university teachers' beliefs about the integration of using technologies in their teaching activities. Previous studies have shown that SE as an individual factor in explaining university teachers' beliefs of using technologies in teaching directly affects their PEU and attitudes toward technology adoption (Kao & Tsai, 2009; Ursavaş et al., 2019; Wang & Wang, 2009). A higher degree of SE implies a greater degree of perceived PEU and ATU, which may lead to use of AI-based applications for teaching. Accordingly, the following research hypotheses are proposed:
H4: SE has a significant positive effect on PEU.
H6: SE has a significant positive effect on ATU.

Moreover, researchers have also pointed out that SE directly links to AN (Kao & Tsai, 2009; Sánchez-Prieto et al., 2017). Some studies have implied that when teachers lack the ability to use new technologies, they may have negative perceptions of the technologies (e.g., anxiety). This could influence their cognition of the functions and their attitude towards using the technologies, which must be guided and assisted by teacher training (Cheok et al., 2017; Sánchez-Prieto et al., 2017). When teachers are more familiar with or more confident in using the technologies, they may find that it is easier to use them to assist with their teaching; on the contrary, if teachers experience frustration or negative feelings, it may then influence their attitude towards the adoption of technologies (Motaghian et al., 2013; Sánchez-Prieto et al., 2017; Wang & Wang, 2009). Thus, the following hypotheses are proposed:
H5: SE has a significant negative effect on AN.
H7: AN has a significant negative effect on ATU.

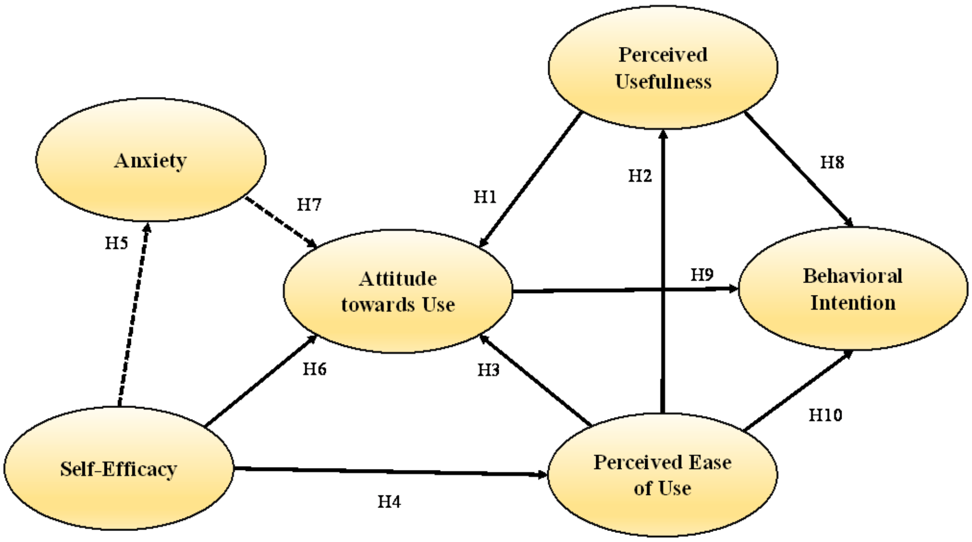

Figure 1. Proposed research model. *Note.* — positive effect, ---- negative effect

3. Method

3.1. The participants

The participants in the present study were university in-service teachers in China. They had the same experience of using AI technologies (e.g., Mosoteach, Smart Class, Youdao Translation, HappyClass Smart Classroom System) and had received the same training courses. The study collected a total of 311 valid questionnaires from 171 male and 140 female participants by excluding the teachers who had no teaching experience or no Internet usage experience as well as the questionnaires with incomplete answers in February and March, 2020. As for age, 45.66% were 30 to 40 years old; 36.01% were 40 to 50 years old; 10.93% were above 50 years old; and 7.40% were under 30 years old.

Figure 2 shows one of the intelligent applications, "Mosoteach" designed for English teachers. The app helps teachers to collect students' work efficiently, and also helps teachers to save the time spent correcting assignments manually in previous teaching contexts. In addition, the app can provide targeted advice to students on how to improve their English writing in detail, which also saves teachers' communication time with each student.

Figure 2. An example of AI-based applications adopted

3.2. Instruments

The present study referred to Davis (1989) and adopted scale items from the previous studies. These items were adapted from published sources that reported a high degree of reliability (Sánchez-Prieto et al., 2017; Teo, 2019; Ursavaş et al., 2019; Wang & Wang, 2009). The instrument includes participants' demographic information and 21 items. These items aim to evaluate participants' belief in the following constructs: PU (four items: e.g., "I think it is useful to learn to adopt AI tools to support teaching"), PEU (three items: e.g., "For me, learning to operate AI tools to support teaching activities is easy"), SE (three items: e.g., "I have the skills required to use AI tools to support teaching"), AN (four items: e.g., "I think it is very difficult to use AI tools to support teaching activities"), ATU (three items: e.g., "For me, learning to operate AI tools to support teaching activities is easy"), BI (four items: e.g., "I will actively learn to adopt AI tools to assist in teaching"). These items were adapted from published sources that reported a high degree of reliability (Sánchez-Prieto et al., 2017; Teo, 2019; Ursavaş et al., 2019; Wang & Wang, 2009).

In order to make the questionnaire content in accordance with the teachers' experience of using AI-based applications in teaching contexts, the present study consulted two professors who are experts in the AI field and two experts who are familiar with the integration of technology into teaching. They helped confirm that all items in the questionnaire were in line with teachers' familiar tone of expression, and could be used to realize teachers' perceptions of and attitudes towards AI tool-supported teaching as a reference for future university teachers to promote AI tools to support teaching activities. The questionnaire in the study adopted a 5-point Likert scale, ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). The preliminary analysis indicated that the factor loadings of four items (i.e., PU4, PEO3, SE3 and ATU3) were lower or had a high correlation with other items in the model. As a result, these items were removed from further analysis; a total of 17 items were used for the following analysis (Appendix A). The final structure showed good internal consistency, reliability, and Cronbach's alpha values; the Cronbach's alpha values are listed in Table 1, and range from .699 to .925.

3.3. Data analysis

The present study employed AMOS in SPSS for the analysis. First of all, the descriptive statistics were conducted to verify the skewness and kurtosis of values and to establish the univariate normality of the data. The critical values were $\pm$3.0 and$\pm$10.0, respectively (Kline, 2010). Furthermore, researchers tested the multivariate normality using Mardia's normalized multivariate kurtosis (Mardia, 1970). Afterwards, confirmatory factor analysis (CFA) was performed to examine the structural validity of the questionnaire. Finally, we verified the path model hypothesized to examine the effects of the influences of university teachers on PU, PEU, SE, AN, ATU and BI of adopting AI tools.

4. Results

4.1. Descriptive statistics

The means, SDs, skewness, and kurtosis values for each of the 17 items in the questionnaire were computed. The mean and standard deviation of AN were 2.842 and .899, respectively. The means of the other constructs were between 3.982 and 4.092 with standard deviations between .550 and .674. This represented participants' positive responses to the items and the mean of values distribution. The values of the skewness and kurtosis for the items were between -1.082 and .427, and -.781 and 3.385, respectively. These values were within the recommended cutoffs of $\pm$3.0 and $\pm$10.0 for skewness and kurtosis, respectively, indicating univariate normality in the data (Kline, 2010). Finally, Mardia's multivariate kurtosis value was calculated as 133.350 and using the Raykov and Marcoulides (2008) formula, p (p+ 2) was calculated as 323. Since the multivariate kurtosis value was smaller than 323, the data showed multivariate normality.

4.2. Test of the measurement model

The present study applied the CFA evaluation model, including the six constructs of PU, PEU, SE, AN, ATU and BI (see Figure 4). The overall model fit evaluation adopted χ^2 and other fit indices such as the Tucker-Lewis index (TLI), the comparative fit index (CFI), root mean square error of approximation (RMSEA), and standardized root mean square residual (SRMR). Hu and Bentler (1999) pointed out that the TLI and CFI values were higher than 0.95, which indicated a good model fit. Also, it was acceptable that RMSEA and SRMR were lower than 0.06 and 0.08, respectively. From the results, the measurement model displayed an acceptable fit to the sample data (χ^2= 194.48; χ^2/df = 1.870; TLI= .967; CFI=.975; RMSEA= .053; SRMR= .037).

Table 1 presents the CFA results; all the factor loadings of the measured items were higher than the threshold value of .60 (ranging from .711 to .922). The Cronbach's alpha values of PU, PEU, SE, AN, ATU and BI were .843, .899, .887, .925, .699 and .916, respectively. The overall reliability of the questionnaire was .809, indicating sufficient internal consistency of the factor items. Moreover, the range of composite reliability (CR) was .719~.925, and the range of average variance extracted (AVE) was .562~.818, indicating that the present study had good convergence validity of the adopted variables. The convergence validity of the variables in the present study all meet the standard (Fornell & Larcker, 1981).

In addition to convergence validity, the square roots of all the AVEs in the present study were greater than their correlation coefficients; therefore, each variable adopted in the study had its discriminant validity (Farrell, 2010) (see Table 2).

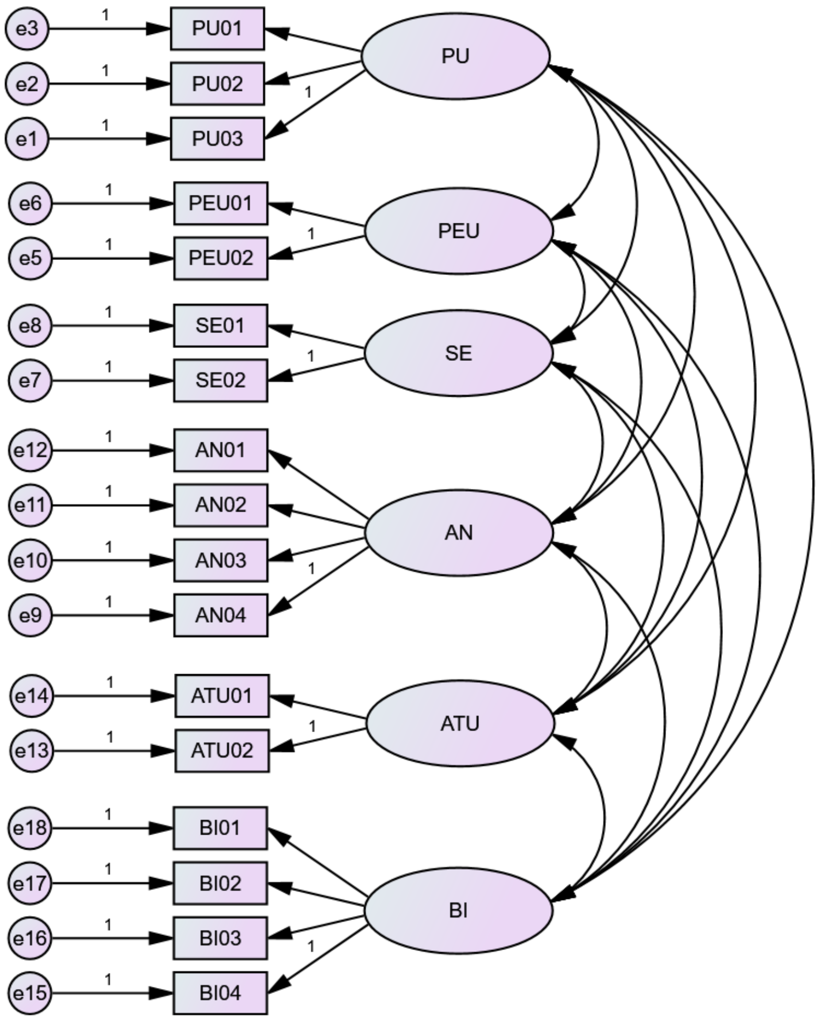

Figure 3. Measurement model with 17 items.

Table 1. Results of the CFA

Items	UE	*t*-value	SE	CR	AVE	Alpha value	Mean	*SD*
PU				0.845	0.646	0.843	4.070	0.636
PU01	1.016	13.134	0.789					
PU02	1.239	13.6	0.868					
PU03#	1.000		0.749					
PEU				0.900	0.818	0.899	4.0482	0.674
PEU01	0.925	17.804	0.886					
PEU02#	1.000		0.922					
SE				0.886	0.796	0.887	3.9823	0.647

SE01	0.969	17.476	0.879					
SE02[#]	1.000		0.905					
AN				0.925	0.755	0.925	2.842	0.899
AN01	0.957	19.37	0.853					
AN02	1.046	20.819	0.888					
AN03	1.019	20.178	0.873					
AN04[#]	1.000		0.862					
ATU				0.719	0.562	0.699	4.092	0.623
ATU01	0.679	11.524	0.711					
ATU02[#]	1.000		0.787					
BI				0.916	0.732	0.916	4.036	0.550
BI01	1.043	19.633	0.851					
BI02	1.021	19.409	0.854					
BI03	1.035	19.459	0.849					
BI04[#]	1.000		0.868					

Note: UE= unstandardized estimate; SE= standardized estimate, factor loadings; PU= perceived usefulness; PEU= perceived ease of use; SE= self-efficacy; AN= anxiety; ATU= attitude towards use; BI= behavioral intention. [*] $p < .01$; [#] this value was fixed at 1.000 for model identification purposes.

Table 2. Correlation coefficient and discriminant validity

	BI	ATU	AN	SE	PEU	PU
BI	(0.856)					
ATU	0.823	(0.750)				
AN	-0.128	-0.307	(0.869)			
SE	0.596	0.666	-0.200	(0.892)		
PEU	0.524	0.640	-0.208	0.654	(0.904)	
PU	0.495	0.439	-0.111	0.426	0.460	(0.804)

Note. Diagonal values shows square root of AVE; PU = perceived usefulness; PEU = perceived ease of use; SE = self-efficacy; AN = anxiety; ATU = attitude towards use; BI = behavioral intention.

4.3. Tests of direct and indirect effects

Results of the test of the structural model showed a good model fit (χ^2= 212.298; χ^2/df = 1.948; TLI= 0.964; CFI= 0.971; RMSEA= .055; SRMR= .048). From the research model (Figure 1), four endogenous constructs were tested. Based on the hypotheses proposed in this study, the bootstrap method was performed for the evaluation. As shown in Table 3, seven out of 10 hypotheses were supported by the data; except for H1, H7 and H10, all the hypotheses were supported in the present study.

Table 3. Hypothesis Testing Results

Hypotheses	Path	Estimate	*t*-value	Bias-corrected		Sig	Result
				Lower	Upper	*p*	
H1	PU→ATU	0.125	1.81	-0.043	0.267	0.146	Not supported
H2	PEU→PU	0.472	7.254	0.321	0.615	0.002	Supported
H3	PEU→ATU	0.279	3.119	0.065	0.508	0.014	Supported
H4	SE→PEU	0.663	11.596	0.566	0.748	0.002	Supported
H5	SE→AN	-0.209	-3.367	-0.339	-0.071	0.003	Supported
H6	SE→ATU	0.437	5.503	0.246	0.611	0.001	Supported
H7	AN→ATU	-0.089	-1.623	-0.202	0.016	0.107	Not supported
H8	PU→BI	0.175	2.881	0.039	0.359	0.012	Supported
H9	ATU→BI	0.793	7.828	0.626	1.003	0.001	Supported
H10	PEU→BI	-0.058	-0.734	-0.297	0.132	0.533	Not supported

Note. PU = perceived usefulness; PEU = perceived ease of use; SE = self-efficacy; AN = anxiety; ATU = attitude towards use; BI = behavioral intention.

Table 4 shows the standardized total effects, as well as the direct and indirect effects of each variable correlated in the model. The sum of direct and indirect effects is total effects. In the model of the present study, the standardized total effects of predictor variables on the dependent variables was between -.209 and .793.

Four endogenous constructs were tested in the model. The coefficient of variation of BI was determined by PU, PEU and ATU, and the explanatory power (R^2) was .704. In other words, AN, SE, PU, PEU and ATU jointly explained 70.4% of BI changes. The most dominant determinant was ATU with a total effect of .793, followed by SE with a total effect of .554, PEU with a total effect of .292, PU with a total effect of .274, and AN with a total effect of -.071.

Among these four endogenous constructs, the highest amount of variance (54.5%) was explained by the determinants of ATU. The most dominant determinant was SE with a total effect of .679, followed by PEU with a total effect of .338, PU with a total effect of .125, and AN with a total effect of -.89. The explained variation of PEU in this model was 43.9%; the most dominant determinant was SE with a total effect of .663. The explained variation of PU was 22.3%; the most dominant determinants were SE and PEU with a total effect of .313 and .472, respectively. The explained variation of AN was 4.4%; the most dominant determinant was SE with a total effect of -.209.

Table 4. Direct, indirect and total effects of the research model

Endogenous variable	Determinant	Standardized estimates		
		Direct	Indirect	Total
AN (R^2 = 0.044)	SE	-0.209	-	-0.209
PU (R^2 = 0.223)	SE	-	0.313	0.313
	PEU	0.472	-	0.472
PEU (R^2 = 0.439)	SE	0.663	-	0.663
ATU (R^2 = 0.545)	AN	-0.089	-	-0.089
	SE	0.437	0.242	0.679
	PU	0.125	-	0.125
	PEU	0.279	0.059	0.338
BI (R^2 = 0.704)	AN	-	-0.071	-0.071
	SE	-	0.554	0.554
	PU	0.175	0.099	0.274
	PEU	-0.058	0.350	0.292
	ATU	0.793	-	0.793

Note. PU = perceived usefulness; PEU = perceived ease of use; SE = self-efficacy; AN = anxiety; ATU = attitude towards use; BI = behavioral intention.

5. Discussion and conclusion

The present study was based on TAM and added teachers' SE and AN about integrating AI tools to examine university teachers' perspectives on AI tool-supported teaching as well as their behavior and influencing factors. Besides, the research model was tested, in which individual differences such as technology AN, SE and relevant factors affecting teachers' acceptance of technology were discussed.

The findings of this study highlight that teachers' SE would positively influence their PEU and ATU about adopting AI technologies, and it could further affect PU through PEU. This is in line with Agudo-Peregrina's et al. study (2014) which revealed the dual nature of perceived usefulness: the component related to efficiency and performance and the component related to flexibility. For instance, teachers would discover that there were differences in efficiency and performance-related advantages of AI tools, and they would also consider the high correlation between the chosen learning strategy and the academic performance (Agudo-Peregrina et al., 2014; Paechter et al., 2010). On the other hand, Bai et al. (2019) illustrated that teachers' SE usually has an indirect effect on their attitude to adopt certain technology in teaching. Chang et al. (2017) also found that the relationship between SE and PU is influenced by PEU. In other words, university teachers' SE would have positive effects on their perceived ease of use, perceived usefulness and attitude toward AI technologies. AI technology for teaching is still in its early stage; thus, most of the teachers still worry whether their ICT skills could meet the needs of integrating artificial intelligence in teaching practice. During the training process, it is necessary to increase their ability and confidence in learning to adopt AI tools, thus making them feel that it is easy to apply them in their teaching. On the other hand, teachers' confidence in using AI technology makes them feel that they have control in the teaching environment, and as such, the application of AI technology is not complicated for them, so they can easily integrate it into their teaching activities

Moreover, teachers' SE and AN were negatively correlated, denoting that teachers with higher SE were less anxious about integrating AI technologies into their teaching (Yeşilyurt et al., 2016). Bai et al. (2019) employed the technology acceptance model, the value-expectancy theory and a learning perspective to discuss the effects of teacher professional development. Researchers have indicated that teachers' ICT self-efficacy would positively affect their continuance intention through their perceptions (i.e., perceived ease of use and perceived usefulness). Also, teachers' ICT anxiety would have negative impacts on their perceived ease of use and continuance intention. Researchers have also reported that anxiety is related to prior unpleasant experiences, and therefore, anxiety could potentially neutralize the effects of PEU (Chavoshi & Hamidi, 2019). In particular, in China, the examination-oriented culture may be an explanation, since most teachers face a heavy workload and they may be concerned with the overtime spent on learning new technology. From the perspective of facilitating the AI technology acceptance of future teachers, it is important to design educational actions that emphasize the usefulness of these AI technologies in teaching and learning practice, and reduce the anxiety they may generate. These points should be taken into account when planning teacher training, which should focus on the pedagogical use of these AI technologies in real teaching and learning environments through the practical activities (Bai et al., 2019; Sánchez-Prieto et al., 2016; Sánchez-Prieto et al., 2017).

Another finding is that the teachers' PEU would positively affect their PU as well as their attitude toward applying AI technologies to support teaching. The findings were consistent with the interaction relationships between PEU, PU and ATU of the technology acceptance research in the educational field (Teo, 2019; Joo et al., 2018). For example, Teo (2019) pointed out that the interaction between PU, PEU, FC and subjective norms had influences on ATU, which then facilitated teachers' intention to use technology. University teachers' perceived ease of use of AI technologies would directly influence the perceived usefulness, and the perceived ease of use of AI technologies had a significant influence on teachers' adoption of AI technologies in teaching. The present study also uncovered that teachers' perceived usefulness of AI technologies and their attitude towards AI technology-supported teaching would have positive effects on their adoption behavior. For instance, Sánchez-Prieto et al. (2017) examined the differences of acceptance between higher education and lifelong learning on the digital learning system, and suggested building up stronger relationships between perceived usefulness and behavioral intention, perceived ease of use and perceived usefulness as well as SE and perceived ease of use.

Some of the hypotheses in this study are not significant. For instance, PU did not have a significant influence on ATU (H1). Raza et al. (2017) had a similar finding of the insignificant impact of PU on ATT to adopt mobile banking. A possible explanation is that university teachers tend to insist on their point of view based on their own experience; thus, PU may easily affect the behavior intention rather than attitude. Besides, AN did not decide their attitude towards use (H7). It is indicated that AN often negatively impacts ATT or BI in the context of education (Hsu, 2009). The significance of the effect of AN on ATT may depend on which situation causes teachers' negative feelings, discomfort or reluctance to adopt AI technologies: subject matters or SE for ICT skills. Thus, introducing a few carefully designed supportive activities in teachers' training programs may help familiarize the teachers with AI technology and raise their comfort levels. Contrary to our expectations, PEU did not have a significant influence on BI (H10). In other words, if AI technologies are not easy to use and apply, even those that are useful for teachers and learners, teachers may remain in their original status or choose other options (Ursavaş et al., 2019). The participants of the current study who had experience of integrating technologies into their teaching practice tended to focus more on perceived usefulness for teaching and learning. In other words, even if some AI technologies are easy to use and apply, without improving the quality of teachers' instruction, it would not significantly change teachers' behavior when adopting these technologies in their teaching activities.

AI technologies can analyze students' learning behavior and performance and provide students with just-in-time guidance and feedback. Moreover, they can also integrate students' individual and learning process data, diagnose students' learning situation, and assist teachers in adjusting the teaching strategies, which then enhance students' learning effectiveness (Hwang, 2014; Hung et al., 2014). The findings of this study specified that university teachers' adoption of AI technologies in their teaching would be influenced by their perceived usefulness and attitude towards AI technologies, for example, how to effectively increase students' learning effectiveness through AI technologies (Hung et al., 2014). One possible explanation is that the information skills of teachers now have a certain degree of training basics; when teachers consider integrating technologies into teaching, they directly take the usefulness of technologies for teaching into consideration, and evaluate whether to adopt or keep employing them (Wang & Wang, 2009).

On the other hand, the ease with which university teachers adopt AI technologies also affects their attitude towards using AI to support teaching. Besides, teachers' perceived ease of use of AI further influences their perceived usefulness as well as their behavior of employing AI to support teaching. In other words, increasing teachers' ease of integrating AI technologies into teaching activities can also enhance their perceived usefulness of AI technology-assisted teaching, and facilitate their adoption behavior. Aside from improving the user interface for using AI technologies, some studies have pointed out that teachers' confidence and ability of using AI technologies could affect their willingness of incorporating AI technologies into their learning designs (Sánchez-Prieto et al., 2017). Based on the research results, educational implications for teacher education in higher education were concluded. Firstly, the results of the study informed the educators and policymakers in higher education that when planning training activities of adopting AI to support teaching for teachers, it is necessary to consider teachers' individual differences and determine effective ways to mitigate teachers' AN or strengthen their SE of adopting AI technologies in teaching. For instance, enhancing teachers' professional development through teacher training or assistance from technology professionals can help teachers spend less time learning how to adopt AI technologies in their teaching (Cheok et al., 2017; Kao & Tsai, 2009; Wang & Wang, 2009). Besides, the use of AI technologies has spread to every corner of modern society; it is therefore necessary to inform teachers who may have diverse educational backgrounds of the basic concepts of Artificial Intelligence and provide convenient AI tools for teachers to integrate into their teaching processes.

The present study has some limitations. In terms of samples, the participants were recruited from among university teachers in China, which may limit the research inference. It is suggested that researchers can further investigate the factors affecting intentions of teachers with different backgrounds and teaching experiences to use AI technologies in school settings in the future. Regarding university teachers' attitudes towards and behavior of adopting AI technologies to support teaching, some external variables can be considered such as social support, subjective norms, and facilitating conditions, to name just a few. Furthermore, future researchers can collect and compare the data from different points in time to understand the effects of the evolution of teachers' attitudes towards AI-supported teaching. Also, future studies can design the intervention experiment and interviews to explore the implementing strategies and application effects of a mixed teaching approach based on a smart learning environment in different teaching contexts to obtain a deeper understanding of its influences on teachers' attitudes towards and perspectives on AI-supported teaching. Moreover, the transformation of the role of university teachers in AI technology-integrated teaching and learning activities (e.g., collaborative learning facilitator, learning evaluator, feedback giver) is also an issue that is worth investigating. Future studies need not only rely on technologies, algorithms and teaching strategies, but should also focus on teachers' adoption attitude toward AI technologies as well as their practice of applying AI in their teaching, which creates a meaningful learning environment.

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