Factors affecting Chinese undergraduate medical students' behavioural intention and actual use of intelligent tutoring systems

Feifei Han
Australian Catholic University

This study examined Chinese undergraduate medical students' acceptance and adoption of intelligent tutoring systems (ITSs) using the general extended technology acceptance model for e-learning via a Likert-scale questionnaire. Specifically, it examined the relations between the five antecedents and the four core components in the model (i.e., perceived usefulness (PU), perceived ease of use (PEOU), behavioural intention and actual use of ITSs). The results of PLS-SEM showed that perceived enjoyment was the most influential antecedent as it significantly impacted both PU and PEOU. Both self-efficacy and prior experience only significantly contributed to PEOU but not PU. Both PU and PEOU significantly and positively predicted behavioural intention, which in turn had a significant and positive path to actual use. The results provide some practical implications to teachers as to how to encourage Chinese undergraduate medical students' adoption of ITSs: by integrating some gamification elements into the learning activities in ITSs to foster students' enjoyable feelings or familiarising students with using ITSs so that they can quickly adapt to learning through them. This could be achieved by providing guidance in using ITSs via videos, websites or booklets, or at the beginning of the course, inviting senior students to share their perceived advantages and usefulness of using ITSs.

Implications for practice or policy:
- Because of the importance of perceived enjoyment, teachers may integrate some gamification into the learning activities in ITSs to nurture students' enjoyable feelings.
- To enable students to quickly accommodate learning via ITSs, institutions may provide students with information on common features of ITSs or how to navigate a specific ITS.
- Teachers may explicitly explain how learning objectives can be better achieved through using an ITSs so that students will appreciate its usefulness.

Keywords: intelligent tutoring systems, extended technology acceptance model, behavioural intention, actual use, Chinese undergraduate medical students, PLS-SEM

Introduction

Over the last few decades, learning and teaching in medical education have undergone significant transformation (De Leeuw et al., 2019). With the ubiquitous utilisation of technology in delivering education to medical students, e-learning has become an indispensable part of contemporary medical education worldwide (Dhir et al., 2017; Kim & Kim, 2019; Shen, 2022), even in low-resource countries (Barteit et al., 2020; Samarasekara, 2022). There are diverse forms of e-learning in medical education, such as flipped classrooms, simulations, multimedia learning, social media learning, mobile learning, gamified learning and intelligent tutoring systems (ITSs) (Regmi & Jones, 2020). In recent years, the rapid advancement of artificial intelligence, machine learning and data mining techniques has led to the increasing adoption of ITSs in many disciplines, including medical education (Mousavinasab et al., 2021). ITSs are computer-based or web-based instruction systems that use artificial intelligence to present students with intelligent help and guidance for self-directed and individualised learning (Karaci et al., 2018). ITSs provide new ways of delivering instruction to students and have many benefits: they allow students to access to learning spaces anytime and anywhere; they provide students with timely feedback; they foster self-directed learning and enhances learning engagement; and they equip students with competencies to become lifelong learners (H. Huang et al., 2022).

ITSs have been used widely in medical education, as they can provide case-based experiential learning, which is especially useful for teaching the interpretation of neuroradiological images (Sharples et al., 2000) or teaching how to detect diagnostic errors in internal medicine (Graber et al., 2005). Furthermore, the interaction and personalisation features in the ITSs are able to simulate authentic clinical situations, which have advantages in training medical students' clinical reasoning skills (Suebnukarn, 2009). Advances in high-fidelity simulations used in ITSs also provide medical residents with new opportunities to practise surgical skills and gain access to objective and immediate feedback (Fazlollahi et al., 2022; Mirchi et al., 2021).

Despite various benefits of ITSs in medical education, there is little research on medical students' acceptance and adoption of ITSs, in particular in the context of medical education in China. The present study aimed to examine how personal factors influence Chinese undergraduate medical students' acceptance and adoption of ITSs. Identifying these factors is important for two reasons. First, ITSs have been increasingly implemented in Chinese medical education to prepare medical graduates with essential lifelong and self-directed learning skills, which are critical for doctors (L. Chen et al., 2023). Furthermore, unlike in the United States of America, where medical degrees are available only at the graduate level (Mowery, 2015), medical degrees in China are offered mostly to secondary school leavers (Ministry of Education of the People's Republic of China, 2020; W. Wang, 2021). Chinese secondary school students receive education mainly through face-to-face classroom teaching (C. Li et al., 2021). Hence, most Chinese undergraduate medical students face challenges when applying various forms of e-learning in both formal and informal studies and may lack essential skills in and experiences of learning through these forms of e-learning, including ITSs. Hence, identifying which factors may influence Chinese undergraduate medical students' acceptance and adoption of ITSs will provide an evidence base for targeted strategies to be developed and implemented in order to more effectively improve Chinese medical students' learning through ITSs.

Theoretical framework of investigating acceptance and adoption of learning technologies

In the literature of technology adoption, a number of theoretical models have been proposed to examine factors influencing an individual's acceptance and adoption of technologies, including the theory of reasoned action (Ajzen & Fishbein, 1977), theory of planned behaviour (Taylor & Todd, 1995), task technology fit (Goodhue & Thompson, 1995), unified theory of acceptance and use of technology (Venkatesh & Bala, 2008) and technology acceptance model (TAM; Davis, 1989).

Of these models, TAM is widely used to investigate students' acceptance and adoption of various learning technologies and e-learning systems (Thongsri et al., 2020). The popularity of using TAM in research on students' acceptance and adoption of learning technologies are two-fold. First, unlike the theory of planned behaviour (Taylor & Todd, 1995) and the unified theory of acceptance and use of technology (Venkatesh & Bala, 2008), which place much emphasis on understanding the social factors and interpersonal interactions on students' acceptance and adoption of technologies or systems, the focus of TAM is on personal factors (Chu & Chen, 2016). Second, TAM has high credibility (Abdullah & Ward, 2016; Lee et al., 2013). Based on their meta-analysis of 88 studies using TAM, King and He (2006) confirmed that TAM is "a valid and robust model" (p. 740).

In the original TAM, the two main constructs are perceived usefulness (PU) and perceived ease of use (PEOU). PU is defined as "the degree to which a person believes that using a particular system would enhance his or her job performance" and PEOU refers to "the degree to which a person believes that using a particular system would be free of effort" (Davis, 1989, p. 320). On the one hand, PU and PEOU are said to influence an individual's behavioural intention (BI) and actual use (AU) of technologies. On the other hand, PU and PEOU are also influenced by many external factors, known as antecedents.

Including the antecedents in TAM is important and meaningful, as without these antecedents, TAM provides only general information on technology acceptance and usage but fails to explain the underlying mechanism as to why or why not a particular technology or system is accepted and used (I. Liu et al., 2010). Venkatesh and Davis (1996) have argued that "in order to be able to explain user acceptance and use, it is important to understand the antecedents of the key TAM constructs, perceived ease of use, and usefulness" (p. 473). Understanding how different antecedents impact users' BI and AU will guide designers and practitioners to "pursue appropriate corrective steps" to improve technologies or systems (Davis et al., 1989, p. 985).

For the above reasons, the original TAM has been further developed by including a large number of antecedents, which has resulted in a diversity of extended TAM (ETAM, He et al., 2021). Even though these diverse ETAMs have suited different research populations and have provided useful information to specific research contexts, they fail to represent a general picture of the factors underpinning the acceptance and adoption of learning technologies and systems. In order to help researchers, educators and designers understand which personal factors are likely to exert influence on users' acceptance of learning technologies and systems, Abdullah and Ward (2016) derived a general extended technology acceptance model for e-learning (GETAMEL). To establish it, they systematically reviewed 107 studies published between 2006 and 2016 and found that 152 antecedents were tested in those studies. To include an antecedent in the GETAMEL, Abdullah and Ward used the criterion that the antecedents should have been tested in at least 10 studies – only five antecedents met the criterion. The five antecedents have not only been frequently examined in various ETAMs but also have been shown to significantly influence users' BI and AU of learning technologies and systems.

The five antecedents were self-efficacy, defined as an individual's belief about his/her ability to perform a specific task using a system (Shen & Eder, 2009); social Influence, defined as a person's perception that most people who are important to him/her think he/she should or should not use a technology or an e-learning systems (Venkatesh et al., 2003); perceived enjoyment, referred to as "the extent to which the activity of using a specific system is perceived to be enjoyable" (Park et al., 2012, p. 379); computer anxiety, referred to as an individual's uneasy, apprehensive or fearful reactions about current or future use of computers or e-learning systems (Venkatesh et al., 2003); and prior experience, defined as an individual's experience related to using computers or e-learning systems (Smith et al., 1999). Based on the frequency of inclusion in previous studies, the five external antecedents were ranked as follows: self-efficacy appeared in 51 studies, followed by social influence and perceived enjoyment, which were examined in 32 and 23 studies, respectively. Computer anxiety was investigated in 19 studies, followed by prior experience with 13 studies.

Abdullah and Ward (2016) calculated the average path coefficients from these five antecedents to PU and PEOU for all types of users, including students, teachers and employees. As the present study focused on students, only the path coefficients for the student population are presented (see Figure 1 for a summary). The average path coefficients from the five antecedents to PU are all positive: perceived enjoyment (.452), social influence (.301), self-efficacy (.174), prior experience (.169) and computer anxiety (.070). As to the average path coefficients from the five factors to PEOU, four out of the five antecedents are positive – self-efficacy (.352), perceived enjoyment (.341), prior experience (.221), and social influence (.195) – with the exception of computer anxiety (-.199), which has a negative path to PEOU.

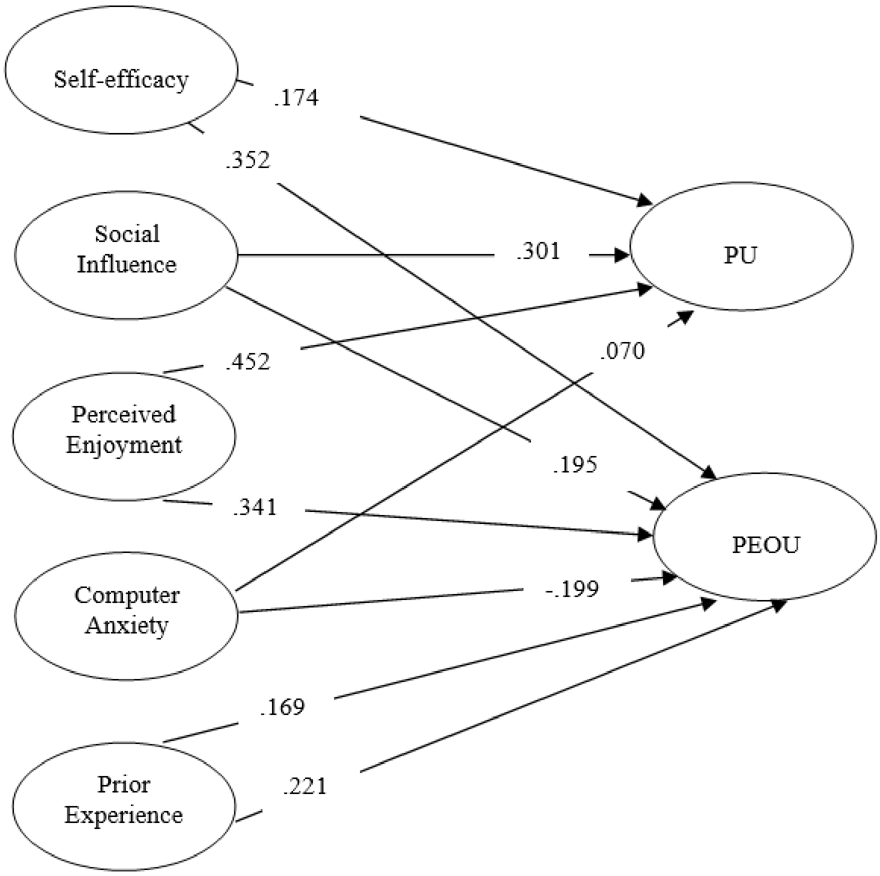

Figure 1. Average path coefficients (β) in the GETAMEL (adapted from Abdullah & Ward, 2016, p. 246)

The GETAMEL has been used to investigate both students' and teachers' acceptance and adoption of various learning technologies and e-learning systems. In a recent review, Strzelecki et al. (2022) identified 10 articles, which included all the five antecedents in the GETAMEL and examined how these antecedents influenced PU and PEOU. These studies were conducted in the contexts of e-portfolio (Abdullah et al., 2016), e-learning (Chang et al., 2017; Cicha et al., 2021; Doleck et al., 2018; Humida et al., 2021; Jiang et al., 2021), mobile applications (Y. Liu et al., 2023), information and communication technologies (Rizun & Strzelecki, 2020) and learning management systems (Matarirano, Jere et al., 2021; Matarirano, Panicker et al., 2021). Although perceived enjoyment and social influence have consistently predicted both PU and PEOU, the paths from self-efficacy, computer anxiety and prior experience to PU are not always significant. These results seem to suggest that the relative contributions from the five antecedents to PU and PEOU may depend on the specific e-learning system or tool being examined. ITSs differ from the vast majority of e-learning systems because they are able to provide personalised instruction, adaptive feedback and automated assessment by leveraging both natural language processing and machine learning algorithms (Bozkurt et al., 2021; Jeon et al., 2023). Hence, empirical studies are needed to examine the influence of the five antecedents on ITSs' acceptance and adoption.

The present study and hypotheses

The present study examined the acceptance and adoption of ITSs among Chinese medical students due to an increasing integration of ITSs in Chinese medical education (L. Chen et al., 2023). Understanding how various personal factors are likely to influence Chinese medical students' acceptance and adoption of ITSs will provide Chinese medical educators actionable knowledge so that strategies can be designed to specifically target one or more factors to improve them with the ultimate aim of helping Chinese medical students learn more effectively through ITSs. Although many personal factors may affect Chinese medical students' acceptance and adoption of ITSs in their learning, the present study focused on the five antecedents (i.e., self-efficacy, social influence, perceived enjoyment, prior experience and computer anxiety) identified in the GETAMEL (Abdullah & Ward, 2016), as these factors have been consistently reported to have significant impacts on the adoption of e-learning technologies in different student population, including Chinese university students (Jiang et al., 2021; Y. Liu et al., 2023).

The present study tested 14 hypotheses based on the GETAMEL and the ETAM:

- Hypothesis 1: Self-efficacy positively affects Chinese medical students’ PU of ITSs.
- Hypothesis 2: Social influence positively affects Chinese medical students’ PU of ITSs.
- Hypothesis 3: Perceived enjoyment positively affects Chinese medical students’ PU of ITSs.
- Hypothesis 4: Computer anxiety positive affects Chinese medical students’ PU of ITSs.
- Hypothesis 5: Prior experience positively affects Chinese medical students’ PU of ITSs.
- Hypothesis 6: PEOU positively affects Chinese medical students’ PU of ITSs.
- Hypothesis 7: Self-efficacy positively affects Chinese medical students’ PEOU of ITSs.
- Hypothesis 8: Social influence positively affects Chinese medical students’ PEOU of ITSs.
- Hypothesis 9: Perceived enjoyment positively affects Chinese medical students’ PEOU of ITSs.
- Hypothesis 10: Computer anxiety negatively affects Chinese medical students’ PEOU of ITSs.
- Hypothesis 11: Prior experience positively affects Chinese medical students’ PEOU of ITSs.
- Hypothesis 12: PU positively affects Chinese medical students’ BI of adopting ITSs.
- Hypothesis 13: PEOU positively affects Chinese medical students’ BI of adopting ITSs.
- Hypothesis 14: BI positively affects Chinese medical students’ AU of ITSs.

Materials and methods

Participants and research context

The present study adopted a cross-sectional design using a self-reported questionnaire. The study was conducted at a Chinese public university specialising in medical sciences in Northwestern China. The participants were recruited from a medical course which used an ITS to supplement student learning. Using the ITS was not compulsory but was highly encouraged by the course coordinator, as the exercises in the ITS were similar to those used in the examinations in the course. The ITS not only provided immediate feedback on the correctness of students’ answers but also was able to guide students to solve problems when their answers were inaccurate. Moreover, the ITS had capacity to show students the link between the exercises and the concepts, which allowed students to extend learning beyond the exercises in the ITS via reading relevant course content or reviewing key learning points.

Altogether, 102 Chinese undergraduate medical students participated in the study. However, two students did not complete the questionnaire, hence were removed from data analysis, resulting in 100 participants in the final data set. Out of 100 participants, 35 were male and 65 were female. Their mean age was 19.31 with a standard deviation of 1.29.

Data collection strictly followed the ethical requirements: students were informed that participation in the study was voluntary and anonymous, and their decision to participate or not would not have any consequences. I was not a staff member at the university where the data was collected and had not been involved in teaching the students who participated in this research.

Instrument

The instrument was a 5-point Likert-scale questionnaire that consisted of 26 items representing eight scales – self-efficacy, social influence, perceived enjoyment, computer anxiety, prior experience, PU, PEOU and BI – and a single item assessing AU. The anchors of the eight scales were 1 representing strongly disagree and 5 representing strongly agree. The single item AU asked students to respond on how frequently they used the ITS in their study, with 1 representing never and 5 representing a lot. The scales were adapted from validated scales used in many studies which examined acceptance and adoption of different types of learning technologies or e-learning systems using the ETAM amongst adult learners (Y. Huang, 2016; Lee et al., 2013; Purnomo & Lee, 2013; Sánchez & Hueros, 2010; Venkatesh & Bala, 2008;

Venkatesh & Davis, 1996). As the GETAMEL used in the current study was also developed based on the ETAM and the current participants were also adult learners, using these scales was considered appropriate.

The adaption took the following steps. First, I used the term “the ITS” to replace other specific technologies used in the original scales. For instance, the specific technology used in the original PU scale was “electronic mail”; the adaption changed “electronic mail” to “the ITS”. Second, the adapted scales were presented to eight students who were studying the same degree in the same university where the current participants were recruited. Students were asked to report the items were not meaningful or uninterpretable; and the items were ambiguous or unclear. Third, the reported items were removed if students commented that the items were not meaningful. For example, previous studies (e.g., Abdullah et al., 2016) used two items to assess AU: “I use the ITS” (1 – never to 5 – a lot) and “The number of hours I spend on the ITS” (1 – never to 5 – a lot of hours); students mentioned that the second item repeated the first item. Hence, the second item was removed. The items were revised if students reported the meaning was uninterpretable or ambiguous. Finally, the revised items were presented to these students again until no further comments were received.

To examine the reliability of the scales, Cronbach’s alphas were calculated and the values of all the scales were above the cutoff standard of .700 (Hair et al., 2010). The definitions of the scales, the number of items in each scale and their reliability are presented in Table 1.

Table 1
Scales used in the study

Scale	Definition	No.	α
Self-efficacy	a student’s belief about his/her ability to perform a specific task using the ITS	4	.864
Social influence	a student’s perceptions that most people who are important to him/her think he/she should or should not use the ITS in learning	3	.840
Perceived enjoyment	the extent to which the activity of using the ITS is perceived to be enjoyable	3	.864
Computer anxiety	a student’s evoked uneasy, apprehensive, or fearful reactions about current or future use of computers or e-learning systems	3	.897
Prior experience	a student’s experience of using computers or e-learning systems	3	.813
PU	the degree to which a student believes that using the ITS would enhance his or her performance in the course	3	.774
PEOU	the degree to which a student believes that using the ITS is free of effort	3	.824
BI	a student’s intention to continue to adopt the ITS in their future learning	3	.896

Data analysis

The partial least squares structural equation modeling (PLS-SEM) was adopted over the covariance-based SEM for the following reasons: PLS-SEM offers solutions with small sample sizes even when models comprise many constructs and a large number of items; the PLS-SEM is relatively robust even a multivariate distribution is not assumed; and PLS-SEM can deal with both exploratory and confirmatory models (Gefen et al., 2000). The analysis was conducted using SmartPLS version 4. I followed the two-step procedure of conducting the PLS-SEM suggested by Hair et al (2010). The first step validated the measurement model by assessing the convergent and discriminant validity of the eight scales. According to Fornell and Larcker (1981), the convergent validity is established if factor loadings of items in their corresponding scale > .500; composite reliability (CR) > .700; and the average variance extracted (AVE) > .500. The discriminant validity is established if AVE’s square root of a scale is larger than its correlation with other scales (Hair et al., 2010).

The second step consisted of a multivariate analysis of the structural relationships to test the aforementioned hypotheses. The coefficients of determination (R^2) and the predictive relevance (Q^2) were used to assess the structural model. To ensure that the values of R^2 were not biased, variance inflation factors (VIFs) were checked for possible collinearity. As recommended by Hair et al. (2017), VIF values close to 3 and lower indicated no collinearity. To interpret R^2, I used the guideline proposed by Chin (1998): R^2 above .670 = substantial explanatory power; R^2 between .670 and .190 = moderate explanatory power; and R^2 below .190 = weak explanatory power. Q^2 values above 0 indicate that the structural model has predictive relevance.

Results

The measurement model

The convergent validity of the measurement model is presented in Table 2. Table 2 shows that all the factor loadings were above .600, well above the suggested .500 (Fornell & Larcker, 1981). Both the values of CR and AVE were also above their recommendation of .700 and .500, suggesting the adequacy of the convergent validity.

Table 2
Convergent validity of the measurement model

	EFF	INF	ENY	ANX	EXP	PU	PEOU	BI
CR	.875	.840	.867	.919	.850	.797	.831	.899
AVE	.711	.840	.787	.828	.727	.690	.741	.828
EFF 1	·780***							
EFF 2	·909***							
EFF 3	·858***							
EFF 4	·820***							
INF 1		·890***						
INF 2		·908***						
INF 3		·812***						
ENY 1			·868***					
ENY 2			·908***					
ENY 3			·885***					
ANX 1				·891***				
ANX 2				·935***				
ANX 3				·903***				
EXP 1					·755***			
EXP 2					·909***			
EXP 3					·885***			
PU 1						·804***		
PU 2						·793***		
PU 3						·891***		
PEOU 1							·844***	
PEOU 2							·816***	
PEOU 3							·918***	
BI 1								·883***
BI 2								·921***
BI 3								·926***

Note. EFF = self-efficacy, INF = social influence, ENY = perceived enjoyment, ANX = computer anxiety, EXP = prior experience.

Table 3
Discriminant validity of the measurement model

	EFF	INF	ENY	ANX	EXP	PU	PEOU	BI
	(.843)							
INF	.506***	(.917)						
ENJ	.378***	.647***	(.887)					
ANX	-.180	-.242*	-.169	(.910)				
EXP	.352***	.385***	.378***	-.013	(.853)			
PU	.379***	.470***	.611***	-.043	.518***	(.931)		
PEOU	.498***	.484***	.559***	-.154	.518***	.660***	(.861)	
BI	.409***	.663***	.710***	-.146	.435***	.726***	.683***	(.910)
AU	.303**	.361***	.408***	-.051	.169	.378***	.305**	.458***

Note. EFF = self-efficacy, INF = social influence, ENY = perceived enjoyment, ANX = computer anxiety, EXP = prior experience, ENJ = perceived enjoyment.
$^{*}p < .050$, $^{**}p < .010$, $^{***}p < .001$.

The discriminant validity of the measurement model is presented in Table 3, which shows that the square root of all the AVEs of a given scale was larger than its correlation coefficients with other scales, suggesting a satisfactory level of discriminant validity.

The structural model

The values of the VIF were between 1.000 and 2. 164, indicating that no collinearity issues were present. Table 4 presents the values of R^2 and Q^2. The R^2 values ranged between .210 and .615, suggesting that the explanatory power to PU, PEOU, BI and AU was moderate. Specifically, the results show that 49.1% of the change in PEOU could be explained by the five antecedents, and 56.2% of change in PU could be attributed to the five antecedents and PEOU. Furthermore, 61.5% of the change in BI and 21.0% of the change in AU could be explained by the research model. Table 4 also shows that the Q^2 values for PU, PEOU, BI and AU were all above 0, hence the predictive relevance of the structural model was established.

Table 4
Values of R^2 and Q^2 of the endogenous variables in the structural model

Variable	R^2	Q^2
PU	.491	.395
PEOU	.562	.397
BI	.615	.475
AU	.210	.129

The path coefficients of the structural model and the results of hypothesis testing are presented in Table 5 and visualised in Figure 2.

Table 5
Path coefficients of the structural model and the results of hypothesis testing

Variable	Path	Variable	β	*p*	Hypothesis	Result
Self-efficacy	→	PU	.015	.973	Hypothesis 1	No
Social influence	→	PU	.033	.757	Hypothesis 2	No
Perceived enjoyment	→	PU	$.314^{*}$	.012	Hypothesis 3	Yes
Computer anxiety	→	PU	-.058	.462	Hypothesis 4	No
Prior experience	→	PU	.206	.068	Hypothesis 5	No
PEOU	→	PU	$.375^{**}$	.002	Hypothesis 6	Yes
Self-efficacy	→	PEOU	$.264^{**}$	.005	Hypothesis 7	Yes
Social influence	→	PEOU	.018	.885	Hypothesis 8	No
Perceived enjoyment	→	PEOU	$.323^{*}$	.012	Hypothesis 9	Yes
Computer anxiety	→	PEOU	-.058	.462	Hypothesis 10	No
Prior experience	→	PEOU	$.297^{*}$	.018	Hypothesis 11	Yes
PU	→	BI	$.499^{***}$	.000	Hypothesis 12	Yes
PEOU	→	BI	$.359^{**}$	.004	Hypothesis 13	Yes
BI	→	AU	$.453^{***}$	.000	Hypothesis 14	Yes

$^{*}p < .050$, $^{**}p < .010$, $^{***}p < .001$.

Results of the paths from the five antecedents and PEOU to PU (Hypotheses 1–6)

Table 5 shows that consistent with Hypothesis 6, PEOU significantly and positively predicted PU (β = .375, *p* < .010). This result means that when students felt that the ITS system was easy to use, they also tended to feel it was useful. Apart from PEOU, however, of the five antecedents, only perceived enjoyment had a significant and positive path to PU (β = .314, *p* < .050), supporting Hypothesis 3. This finding suggests that the more enjoyable feelings students had when using the ITS in their study of course materials, the more likely they perceived the ITS to be useful.

Results of the paths from the five antecedents to PEOU (Hypotheses 7–11)

For the predictions of the five antecedents to PEOU, three out of five factors significantly and positively predicted PEOU: self-efficacy (β = .264, *p* < .010), perceived enjoyment (β = .323, *p* < .050), and prior experience (β = .297, *p* < .050). These results supported Hypotheses 7, 9 and 11. Of the three significant predictors, perceived enjoyment had the highest coefficient, and self-efficacy had the lowest. These results suggest that when students were more confident about their skills in using a computer to perform a task, when they gained more enjoyment in using the ITS or when they were experienced in using computers or e-learning systems in learning, they tended to perceive that using ITSs was easy.

Results of the paths from PU and PEOU to BI (Hypotheses 12 and 13)

The present study found significant paths from PU to BI (β = .499, *p* < .001), and from PEOU to BI (β = .359, *p* < .010), supporting Hypotheses 12 and 13.

Results of the path from BI to AU (Hypothesis 14)

Table 5 further shows that the path from BI to AU was significant and positive (β = .453, *p* < .001); Hypothesis 14 was also supported.

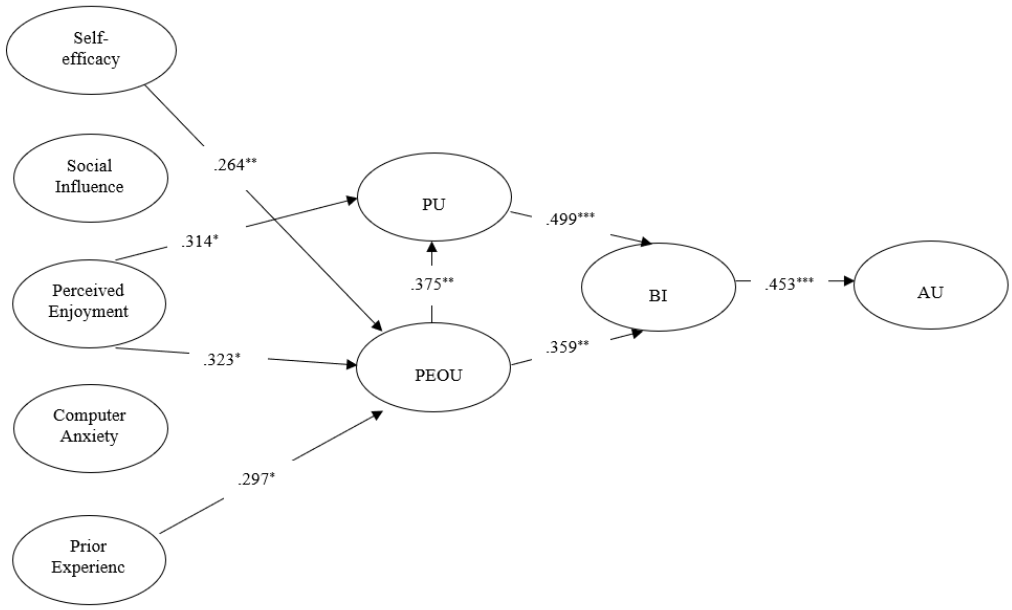

Figure 2. Path coefficients of the structural model (only significant paths are displayed)
$^{*}p < .050$, $^{**}p < .010$, $^{***}p < .001$.

Discussion

The present study adopted the GETAMEL (Abdullah & Ward, 2016) to understand the influence of the five important personal antecedents on BI and AU of the ITSs among Chinese undergraduate medical students. In accordance with the hypotheses derived from the GETAMEL, both PU and PEOU significantly and positively predicted BI, which in turn significantly and positively predicted AU. This finding is understandable, as Chinese medical students face great academic pressure and a heavy academic workload (Mao et al., 2019; Shao et al., 2020), hence, they may choose to use learning technologies, such as the ITSs, that they perceive to be useful and effective in helping them meet the high academic standards and requirements in their studies. In this specific research context, even though using the ITS was not a course requirement but only a supplementary learning tool, many students still used it to facilitate their learning when they believed that the ITS would improve their learning performance in the course.

Corroborated with previous studies (Abdullah et al., 2016; Chang et al., 2017), we also found a significant and positive path from PEOU to BI, demonstrating the importance of the user-friendly design and features of e-learning technologies in users' acceptance and adoption. When Chinese medical students perceived that the use of the ITS did not require much effort to learn, they were more likely to continue to use it. For Chinese medical educators, these results suggest that when selecting an ITS, they should try it or ask some students to trial it to make sure that it is easy to navigate. It is similarly important for designers of ITSs to take into account feedback from student users when designing the interface and features of an ITS in order to provide them a user-friendly experience (H. Huang et al., 2022). The finding that PEOU significantly and positively impacted PU also echoed a number of previous studies (Abdullah et al., 2016; Cao et al., 2020; C. Wang et al., 2020), demonstrating that students who handled the ITS without much effort also tended to attach value to it.

As with Abdullah et al.'s (2016) study, when the five antecedents were examined together, not every factor contributed significantly to PU or PEOU. We found that only perceived enjoyment significantly predicted both PU and PEOU, suggesting that Chinese medical students' positive and enjoyable emotions evoked in using an ITS influenced their beliefs of its usefulness and ease of use. Other studies also found the positive effect of perceived enjoyment on students' acceptance and adoption of different learning technologies or e-learning systems (F. Li et al., 2021; Ni & Cheung, 2023; Venkatesh et al., 2003).

Also corroborating a number of previous studies (Abbad et al., 2009; Abdullah et al., 2016; Lau & Woods, 2008; Lee et al., 2011), the present study found that both prior experience and self-efficacy significantly predicted PEOU. However, the paths from prior experience and self-efficacy to PU were not statistically significant. The non-significant paths could be due to PEOU' significant and positive contribution to PU in the model.

Furthermore, neither this study nor that of Abdullah et al. (2016) found significant paths from computer anxiety to PU or PEOU, which contradicts some studies (e.g., Calisir et al., 2014; H. Chen & Tseng, 2012). A closer examination of these studies showed that they were conducted approximately 10 years ago, when computer use was not as ubiquitous as in recent years. It is likely that the participants in this study did not experience much anxiety when using computers, as computers appear in almost every aspect of people's daily life nowadays (Althubaiti et al., 2022). As a result, computer anxiety did not exert a strong influence on Chinese medical students' decisions with regard to acceptance and adoption of the ITS in their learning.

Similar to computer anxiety, social influence neither significantly predicted PU nor PEOU. A possible reason for the non-significant path from social influence to PU could be that the ITS did not have tools for communication. Abbad et al. (2009) have argued that if an e-learning system or learning technology does not serve as a communication channel, social influence tends to have little impact on students' PU.

The non-significant prediction from social influence to PEOU found in the present study is in line with a number of previous studies (Binyamin et al., 2018; Chang et al., 2017). A possible explanation could be that PEOU tends to be related more to students' own confidence, experience and competence rather than factors external to students, such as the opinions of others (Zhao et al., 2021). Indeed, the present study showed that self-efficacy was a significant predictor of PEOU, suggesting that when students felt confident about their abilities of performing tasks using the ITS, they tended to perceive using the ITS was relatively easy. This finding aligns with that of studies on university students' acceptance and adoption of learning technologies from different academic disciplines, such as computer science (Abdullah et al., 2016), nursing (Chow et al., 2012) and engineering (Ifinedo, 2006).

Implications of the study

With the constant advancement of science and technology, future doctors must keep abreast with an ever-changing health care environment by continuous learning throughout their professional careers. Therefore, a critical component of medical education is to equip medical students with lifelong and self-directed learning capacities (Becker et al., 2020). Integrating ITSs in learning is an emerging paradigm to nurture medical students' lifelong and self-directed learning (L. Chen et al., 2023). To ensure that medical students obtain effective learning outcomes through using ITSs, an important prerequisite is that they are willing to accept and adopt ITSs in their learning. In this respect, the results of the present study are useful for Chinese medical institutions and educators to design appropriate and targeted strategies to enhance Chinese undergraduate medical students' acceptance and adoption of ITSs in their learning.

The present study demonstrated that Chinese undergraduate medical students' perceived enjoyment is an important factor, as it significantly predicts both PU and PEOU, which may in turn lead to increased BI and AU of the ITSs. Research has shown that adding gamification elements into learning activities is able to foster students' enjoyment in learning (Ni & Cheung, 2023; Zhao et al., 2021). Hence, Chinese medical educators and instructional designers should consider integrating some game mechanism into the ITSs to make learning with them an enjoyable experience. In particular, medical educators may consider selecting educational games which have rewards system, as they tend to generate long-term positive effect in medical education (Ghelfenstein-Ferreira et al., 2021; Nicolaidouetal., 2015). In these games, medical students are motivated to solve more difficult questions, which will earn them badges or progress bars (Sardi et al., 2017). In addition, as learners bring various levels of skills, experiences of technologies and different learning styles to learning, educators should try to select games which require a diverse set of abilities (e.g., as speed, accuracy and visual interpretation) to appeal to a wider student population (Krishnamurthy et al., 2022).

Furthermore, the results show that students' self-efficacy and prior experience are significant predictors of PEOU. As the majority of Chinese medical students are undergraduates who have only limited experience in using e-learning systems, including using ITSs in their secondary school learning (F. Li et al., 2021), it is essential that Chinese medical institutions provide sufficient guidance for students, especially in their first year, so that students can quickly adapt to learning through ITSs and build their confidence when using them in their learning. For instance, institutions could use short videos, interactive websites or booklets which present essential information on the common features of ITSs and/or specific information of how to navigate a particular ITS.

As PU had relatively strong impact on Chinese undergraduate medical students' BI, teachers of courses that involve ITSs should explicitly explain how the learning objectives can be better achieved through using ITSs so that students can appreciate the usefulness of using them in their studies. Alternatively, senior students could be invited during orientation or at the beginning of a course to share their perceived usefulness and positive experience of how they have used ITSs to assist their learning.

The key results and the implications related to the key results are summarised in Table 6 for Chinese medical educator as take-home notes.

Table 6
Summary of the implications of the study according to the key results

Key results	Implications
Perceived enjoyment was a significant predictor to both PU and PEOU.	integrating gamification elements into ITSs
Self-efficacy and prior experience were significant predictors of PEOU.	providing essential information for first-year students on features of ITSs and how to navigate them
PU had strong impact on BI.	inviting senior students to share their perceived usefulness and positive experience of using ITSs to assist their medical learning

Limitations of the study and future direction

Several limitations of the present study should be pointed out and may be addressed in future research. First, the current study is a cross-sectional study, which did not examine students' possible changes in their BI and AU of ITSs. In the literature, the limited longitudinal research has demonstrated that students' intention to use learning technologies varies over time (Unal & Uzun, 2021; Zhu et al., 2023). This suggests that the significant personal factors revealed in this cross-sectional study may not be able to sustain Chinese medical students' continuance of using ITSs in their learning. For instance, due to novelty effect, students' enjoyable emotions gained through gamification elements integrated into the ITSs may wear off over time. Hence, future studies should investigate the longitudinal pattern between these antecedents and Chinese medical students' continued intention of using ITSs in an extended period.

Moreover, this study investigated only a limited range of student personal factors on the acceptance and adoption of ITSs. Research has demonstrated that other personal factors, like motivation (Azizi et al., 2020; Chu & Chen, 2016) and digital literacy (He et al., 2021), and non-personal factors, including the quality of an e-learning system (Y. Li et al., 2012; Salloum et al., 2019), types of instructional design (Alshammari et al., 2016), course quality (Cao et al., 2020) and institutions' technical support (Yan et al., 2021), can also affect students' decisions regarding acceptance and adoption of learning technologies or e-learning systems. Therefore, future studies should examine a wider range of student personal and non-personal factors, and the interaction between these factors on Chinese undergraduate medical students' acceptance and adoption of ITSs.

References

Abbad, M. M., Morris, D., & De Nahlik, C. (2009). Looking under the bonnet: Factors affecting student adoption of e-learning systems in Jordan. *International Review of Research in Open and Distributed Learning*, *10*(2). https://doi.org/10.19173/irrodl.v10i2.596

Abdullah, F., & Ward, R. (2016). Developing a general extended technology acceptance model for e-learning (GETAMEL) by analysing commonly used external factors. *Computers in Human Behavior*, *56*, 238–256. https://doi.org/10.1016/j.chb.2015.11.036

Abdullah, F., Ward, R., & Ahmed, E. (2016). Investigating the influence of the most commonly used external variables of TAM on students' perceived ease of use (PEOU) and perceived usefulness (PU) of e-portfolios. *Computers in Human Behavior*, *63*, 75–90. https://doi.org/10.1016/j.chb.2016.05.014

Ajzen, I., & Fishbein, M. (1977). Attitude-behavior relations: A theoretical analysis and review of empirical research. *Psychological Bulletin*, *84*(5), 888–918. https://doi.org/10.1037/0033-2909.84.5.888

Alshammari, S. H., Ali, M. B., & Rosli, M. S. (2016). The influences of technical support, self-efficacy and instructional design on the usage and acceptance of LMS: A comprehensive review. *Turkish Online Journal of Educational Technology*, *15*(2), 116–125. http://tojet.net/articles/v15i2/15213.pdf

Althubaiti, A., Tirksstani, J. M., Alsehaibany, A. A., Aljedani, R. S., Mutairii, A. M., & Alghamdi, N. A. (2022). Digital transformation in medical education: Factors that influence readiness. *Health Informatics Journal*, *28*(1). https://doi.org/10.1177/14604582221075554

Azizi, S. M., Roozbahani, N., & Khatony, A. (2020). Factors affecting the acceptance of blended learning in medical education: Application of UTAUT2 model. *BMC Medical Education, 20*, Article 367. https://doi.org/10.1186/s12909-020-02302-2

Barteit, S., Guzek, D., Jahn, A., Bärnighausen, T., Jorge, M. M., & Neuhann, F. (2020). Evaluation of e-learning for medical education in low-and middle-income countries: A systematic review. *Computers & Education*, *145*, Article 103726. https://doi.org/10.1016/j.compedu.2019.103726

Becker, A., Friedrichs, K., Stiles, M., Herold, K., & Seibert, C. (2020). The clumsy horse: A professional development tool for facilitators of self-directed, case-based learning. *MedEdPORTAL*, *16*, Article 10901. https://doi.org/10.15766/mep_2374-8265.10901

Binyamin, S., Rutter, M., & Smith, S. (2018). The influence of computer self-efficacy and subjective norms on the students' use of learning management systems at King Abdulaziz University. *International Journal of Information and Education Technology*, *8*(10), 693–699. https://doi.org/10.18178/ijiet.2018.8.10.1124

Bozkurt, A., Karadeniz, A., Baneres, D., Guerrero-Roldán, A. E., & Rodríguez, M. E. (2021). Artificial intelligence and reflections from educational landscape: A review of AI studies in half a century. *Sustainability, 13*(2), Article 800. https://doi.org/10.3390/su13020800

Calisir, F., AltinGumussoy, C., Bayraktaroglu, A., & Karaali, D. (2014). Predicting the intention to use a web-based learning system: Perceived content quality, anxiety, perceived system quality, image, and the technology acceptance model. *Human Factors and Ergonomics in Manufacturing & Service Industries, 24*(5), 515–531. https://doi.org/10.1002/hfm.20548

Cao, W., Fang, Z., Hou, G., Han, M., Xu, X., Dong, J., & Zheng, J. (2020). The psychological impact of the COVID-19 epidemic on college students in China. *Psychiatry Research, 287*, Article 112934. https://doi.org/10.1016/j.psychres.2020.112934

Chang, C. T., Hajiyev, J., & Su, C. (2017). Examining the students' behavioural intention to use e-learning in Azerbaijan? The general extended technology acceptance model for e-learning approach. *Computers & Education*, *111*, 128–143. https://doi.org/10.1016/j.compedu.2017.04.010

Chen, H., & Tseng, H. (2012). Factors that influence acceptance of web-based elearning systems for the in-service education of junior high school teachers in Taiwan. *Evaluation and Program Planning, 35*(3), 398–406. https://doi.org/10.1016/j.evalprogplan.2011.11.007

Chen, L., Tang, X.J., Liu, Q., & Zhang, X. (2023). Self-directed learning: Alternative for traditional classroom learning in undergraduate ophthalmic education during the COVID-19 pandemic in China. *Heliyon*, *9*(5). https://doi.org/10.1016/j.heliyon.2023.e15632

Cicha, K., Rizun, M., Rutecka, P., & Strzelecki, A. (2021). Covid-19 and higher education: First-year students' expectations toward distance learning. *Sustainability*, *13*(4), 1–20. https://doi.org/10.3390/su13041889

Chin, W. (1998). The partial least squares approach for structural equation modeling. In G.A. Marcoulides (Ed.), *Modern methods for business research* (pp. 295–336). Lawrence Erlbaum Associates.

Chow, M., Herold, D., Choo, T., & Chan, K. (2012). Extending the technology acceptance model to explore the intention to use Second Life for enhancing healthcare education. *Computers & Education*, *59*(4), 1136–1144. https://doi.org/10.1016/j.compedu.2012.05.011

Chu, T.-H., & Chen, Y.-Y. (2016). With good we become good: Understanding e-learning adoption by theory of planned behavior and group influences. *Computers & Education, 92-93*, 37–52. https://doi.org/10.1016/j.compedu.2015.09.013

Davis, F. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 319–340. https://doi.org/10.2307/249008

Davis, F., Bagozzi, R., & Warshaw, P. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management Science, 35*(8), 982–1003. https://doi.org/10.1287/mnsc.35.8.982

De Leeuw, R., De Soet, A., Van Der Horst, S., Walsh, K., Westerman, M., & Scheele, F. (2019). How we evaluate postgraduate medical e-learning: Systematic review. *JMIR Medical Education*, *5*(1), Article e13128. https://doi.org/10.2196/13128

Dhir, S.K., Verma, D., Batta, M., & Mishra, D. (2017). E-learning in medical education in India. *Indian Paediatrics*, *54*, 871–877. https://doi.org/10.1007/s13312-017-1152-9

Doleck, T., Bazelais, P., & Lemay, D. J. (2018). Is a general extended technology acceptance model for elearning generalizable? *Knowledge Management and E-Learning*, *10*(2), 133–147. https://doi.org/10.34105/j.kmel.2018.10.009

Fazlollahi, A. M., Bakhaidar, M., Alsayegh, A., Yilmaz, R., Winkler-Schwartz, A., Mirchi, N., Langleben, I., Ledwos, N., Sabbagh, A. J., Bajunaid, K., Harley, J. M., & Del Maestro, R. F. (2022). Effect of artificial intelligence tutoring vs expert instruction on learning simulated surgical skills among medical students: A randomized clinical trial. *JAMA Network Open*, *5*(2), Article 2149008. https://jamanetwork.com/journals/jamanetworkopen/fullarticle/2789268

Fornell, C., & Larcker, D. F. (1981). Structural equation models with unobservable variables and measurement error: Algebra and statistics. *Journal of Marketing Research, 18*(1), 382–388. https://doi.org/10.1177/002224378101800104

Gefen, D., Straub, D., & Boudreau, M. C. (2000). Structural equation modeling and regression: Guidelines for research practice. *Communications of the Association for Information Systems, 4*(1), 10–76. https://doi.org/10.1.1.25.781

Ghelfenstein-Ferreira, T., Beaumont, A.L., Dellière, S., Peiffer-Smadja, N., Pineros, N., Carbonnelle, E., Greub, G., Abbara, S., Luong Nguyen, L. B., & Lescat, M. (2021). An educational game evening for medical residents: A proof of concept to evaluate the impact on learning of the use of games. *Journal of Microbiology & Biology Education, 22*(2), Article e00119-21. https://doi.org/10.1128/jmbe.00119-21

Goodhue, D. L., & Thompson, R. L. (1995). Task-technology fit and individual performance. *MIS Quarterly*, *19*(2), 213–236. https://doi.org/10.2307/249689

Graber, M.L., Franklin, N., & Gordon, R. (2005). Diagnostic error in internal medicine. *Archives of Internal Medicine, 165*(13), 1493–1499. https://10.1001/archinte.165.13.1493

Hair, J., Black, W., Babin, B., & Anderson, R. (2010). *Multivariate data analysis* (7th ed.). Prentice Hall.

He, T., Huang, Q., Yu, X., & Li, S. (2021). Exploring students' digital informal learning: the roles of digital competence and DTPB factors. *Behaviour & Information Technology*, *40*(13), 1406–1416. https://doi.org/10.1080/0144929X.2020.1752800

Huang, H., Chen, Y., & Rau, P. (2022). Exploring acceptance of intelligent tutoring system with pedagogical agent among high school students. *Universal Access in the Information Society, 21*(3), 381–392. https://doi.org/10.1007/s10209-021-00835-x

Huang, Y. (2016). The factors that predispose students to continuously use cloud services: Social and technological perspectives. *Computers & Education*, *97*, 86–96. https://doi.org/10.1016/j.compedu.2016.02.016

Humida, T., Al Mamun, M. H., & Keikhosrokiani, P. (2022). Predicting behavioral intention to use e-learning system: A case-study in Begum Rokeya University, Rangpur, Bangladesh. *Education and Information Technologies*, *27*(2), 2241–2265. https://doi.org/10.1007/s10639-021-10707-9

Ifinedo, P. (2006). Acceptance and continuance intention of web-based learning technologies (WLT) use among university students in a Baltic country. *The Electronic Journal of Information Systems in Developing Countries, 23*(6), 1–20. https://doi.org/10.1002/j.1681-4835.2006.tb00151.x

Jeon, J., Lee, S., & Choe, H. (2023). Beyond ChatGPT: A conceptual framework and systematic review of speech-recognition chatbots for language learning. *Computers & Education, 206*, Article 104898. https://doi.org/10.1016/j.compedu.2023.104898

Jiang, M. Y. C., Jong, M. S. Y., Lau, W. W. F., Meng, Y. L., Chai, C. S., & Chen, M. (2021). Validating the general extended technology acceptance model for e-learning: Evidence from an online English as a foreign language course amid COVID-19. *Frontiers in Psychology*, *12*, Article 671615. https://doi.org/10.3389/fpsyg.2021.671615

Karaci, A., Piri, Z., Akyüz, H., & Bilgiici, G. (2018). Student perceptions of an intelligent tutoring system: A technology acceptance model perspective. *International Journal of Computer Applications*, *182*(22), 31–36.

Kim, K., & Kim, G. (2019). Development of e-learning in medical education: 10 years' experience of Korean medical schools. *Korean Journal of Medical Education*, *31*(3), 205–214. https://doi.org/10.3946/kjme.2019.131

King, W., & He, J. (2006). A meta-analysis of the technology acceptance model. *Information& Management, 43*(6), 740–755. https://doi.org/10.1016/j.im.2006.05.003

Krishnamurthy, K., Selvaraj, N., Gupta, P., Cyriac, B., Dhurairaj, P., Abdullah, A., Krishnapillai, A., Lugova, H., Haque, M., Xie, S., & Ang, E. T. (2022). Benefits of gamification in medical education. *Clinical Anatomy*, *35*(6), 795–807. https://doi.org/10.1002/ca.23916

Lau, S., & Woods, P. (2008). An empirical study of learning object acceptance in multimedia learning environment. *Communications of the IBIMA, 5*(1), 1–6. https://ibimapublishing.com/articles/CIBIMA/2008/391054/391054.pdf

Lee, Y., Hsieh, Y., & Chen, Y. (2011). An investigation of employees' use of e-learning systems: Applying the technology acceptance model. *Behaviour and Information Technology, 32*(2), 173–189. https://doi.org/10.1080/0144929X.2011.577190

Lee, Y., Hsieh, Y., & Ma, C. (2013). A model of organizational employees' e-learning systems acceptance. *Knowledge-based Systems, 24*(3), 355–366. https://doi.org/10.1016/j.knosys.2010.09.005

Li, C., He, L., & Wong, I. (2021). Determinants predicting undergraduates' intention to adopt e-learning for studying English in Chinese higher education context: A structural equation modelling approach. *Education and Information Technologies*, *26*, 4221–4239. https://doi.org/10.1177/002224378101800104

Li, F., Jin, T., Edirisingha, P., & Zhang, X. (2021). School-aged students' sustainable online learning engagement during COVID-19: Community of inquiry in a Chinese secondary education context. *Sustainability*, *13*(18), Article 10147. https://doi.org/10.3390/su131810147

Li, Y., Duan, Y., Fu, Z., & Alford, P. (2012). An empirical study on behavioural intention to reuse e-learning systems in rural China. *British Journal of Educational Technology*, *43*(6), 933–948. https://doi.org/10.1111/j.1467-8535.2011.01261.x

Liu, I., Chen, M., Sun, Y., Wible, D., & Kuo, C. (2010). Extending the TAM model to explore the factors that affect intention to use an online learning Community. *Computers & Education, 54*(2), 600–610. https://doi.org/10.1016/j.compedu.2009.09.009

Liu, Y., Sun, J.C.Y., & Chen, S.K. (2023). Comparing technology acceptance of AR-based and 3D map-based mobile library applications: A multigroup SEM analysis. *Interactive Learning Environments*, *31*(7), 4156–4170. https://doi.org/10.1080/10494820.2021.1955271

Mao, Y., Zhang, N., Liu, J., Zhu, B., He, R., & Wang, X. (2019). A systematic review of depression and anxiety in medical students in China. *BMC Medical Education*, *19*(1), 1–13. https://doi.org/10.1186/s12909-019-1744-2

Matarirano, O., Jere, N., Sibanda, H., & Panicker, M. (2021). Antecedents of blackboard adoption by lecturers at a South African higher education institution–Extending GETAMEL. *International Journal of Emerging Technologies in Learning*, *16*(1), 60–79. https://www.learntechlib.org/p/218653/
Matarirano, O., Panicker, M., Jere, N. R., & Maliwa, A. (2021). External factors affecting blackboard learning management system adoption by students: Evidence from a historically disadvantaged higher education institution in South Africa. *South African Journal of Higher Education*, *35*(2), 188–206. https://doi.org/10.20853/35-2-4025
Ministry of Education of the People's Republic of China. (2020). *Accreditation of clinical medical education in China: Review and prospect*. http://www.moe.gov.cn/jyb_xwfb/moe_2082/zl_2020n/2020_zl34/202006/t20200623_467928.html
Mirchi, N., Ledwos, N., & Del Maestro, R.F. (2021). Intelligent tutoring systems: Re-envisioning surgical education in response to COVID-19. *Canadian Journal of Neurological Sciences*, *48*(2), 198–200. https://doi.org/10.1017/cjn.2020.202
Mousavinasab, E., Zarifsanaiey, N., Niakan Kalhori, S., Rakhshan, M., Keikha, L., & Ghazi Saeedi, M. (2021). Intelligent tutoring systems: A systematic review of characteristics, applications, and evaluation methods. *Interactive Learning Environments*, *29*(1), 142–163. https://doi.org/10.1080/10494820.2018.1558257
Mowery, Y. (2015). A primer on medical education in the United States through the lens of a current resident physician. *Annals of Translational Medicine*, *3*(18), Article 270. https://doi.org/10.3978/j.issn.2305-5839.2015.10.19
Ni, A., & Cheung, A. (2023). Understanding secondary students' continuance intention to adopt AI-powered intelligent tutoring system for English learning. *Education and Information Technologies, 28*(10), 3191–3216. https://doi.org/10.1007/s10639-022-11305-z
Nicolaidou, I., Antoniades, A., Constantinou, R., Marangos, C., Kyriacou, E., Bamidis, P., Dafli, E., & Pattichis, C. S. (2015). A virtual emergency tele-medicine serious game in medical training: A quantitative, professional feedback informed evaluation study. *Journal of Medical Internet Research, 17*(6), Article e150. https://doi.org/10.2196/jmir.3667
Park, Y., Son, H., & Kim, C. (2012). Investigating the determinants of construction professionals' acceptance of web-based training: An extension of the technology acceptance model. *Automation in Construction*, *22*, 377–386. https://doi.org/10.1016/j.autcon.2011.09.016
Purnomo, S., & Lee, Y. (2013). E-learning adoption in the banking workplace in Indonesia: An empirical study. *Information Development, 29*(2), 138–153. https://doi.org/10.1177/0266666912448258
Regmi, K., & Jones, L. (2020). A systematic review of the factors–enablers and barriers–affecting e-learning in health sciences education. *BMC Medical Education*, *20*(1), 1–18. https://doi.org/10.1186/s12909-020-02007-6
Rizun, M., & Strzelecki, A. (2020). Students' acceptance of the COVID-19 impact on shifting higher education to distance learning in Poland. *International Journal of Environmental Research and Public Health*, *17*(18), Article 6468. https://doi.org/10.3390/ijerph17186468
Salloum, S., Alhamad, A., Al-Emran, M., Monem, A., & Shaalan, K. (2019). Exploring students' acceptance of e-learning through the development of a comprehensive technology acceptance model. *IEEE Access*, *7*, 128445–128462. https://doi.org/10.1109/ACCESS.2019.2939467
Samarasekara, K. (2022). e-Learning in medical education in Sri Lanka: Survey of medical undergraduates and new graduates. *JMIR Medical Education*, *8*(1), Article e22096. https://doi.org/10.2196/22096
Sánchez, R., & Hueros, A. (2010). Motivational factors that influence the acceptance of Moodle using TAM. *Computers in Human Behavior*, *26*(6), 1632–1640. https://doi.org/10.1016/j.chb.2010.06.011
Sardi, L., Idri, A., & Fernández-Alemán, J. L. (2017). A systematic review of gamification in e-health. *Journal of Biomedical Informatics,71*, 31–48. https://doi.org/10.1016/j.jbi.2017.05.01
Shao, R., He, P., Ling, B., Tan, L., Xu, L., Hou, Y., Kong, L., & Yang, Y. (2020). Prevalence of depression and anxiety and correlations between depression, anxiety, family functioning, social support and coping styles among Chinese medical students. *BMC Psychology*, *8*(1), 1–19. https://doi.org/10.1186/s40359-020-00402-8

Sharples, M., Jeffery, N. P., du Boulay, B., Teather, B. A., Teather, D., & du Boulay, G. H. (2000). Structured computer-based training in the interpretation of neuroradiological images. *International Journal of Medical Informatics, 60*(3), 263–280. https://doi.org/10.1016/S1386-5056(00)00101-5

Shen, J. (2022). Introduction of social media to aid active-learning in medical teaching. *Interactive Learning Environments*, *30*(10), 1932–1939. https://doi.org/10.1080/10494820.2020.1766508

Shen, J., & Eder, L. B. (2009). Intentions to use virtual worlds for education. *Journal of Information Systems Education, 20*(2), 225–233. https://jise.org/volume20/n2/JISEv20n2p225.pdf

Smith, B., Caputi, P., Crittenden, N., Jayasuriya, R., & Rawstorne, P. (1999). A review of the construct of computer experience. *Computers in Human Behavior, 15*(2), 227–242. https://doi.org/10.1016/S0747-5632(99)00020-5

Strzelecki, A., Cicha, K., Rizun, M., & Rutecka, P. (2022). Using a general extended technology acceptance model for e-learning (GETAMEL): A literature review of empirical studies. In R. A. Buchmann, G. C. Silaghi, D. Bufnea, V. Niculescu, G. Czibula, C. Barry, M. Lang, H. Linger, & C. Schneider (Eds.), *Proceedings of the 30th International Conference on Information Systems Development*. International Conference on Information Systems Development. https://aisel.aisnet.org/cgi/viewcontent.cgi?article=1416&context=isd2014

Suebnukarn, S. (2009). Intelligent tutoring system for clinical reasoning skill acquisition in dental students. *Journal of Dental Education*, *73*(10), 1178–1186. https://doi.org/10.1002/j.0022-0337.2009.73.10.tb04809.x

Taylor, S., & Todd, P. (1995). Understanding information technology usage: A test of competing models. *Information Systems Research*, *6*(2), 144–176. https://doi.org/10.1287/isre.6.2.144

Thongsri, N., Shen, L., & Bao, Y. (2020). Investigating academic major differences in perception of computer self-efficacy and intention toward e-learning adoption in China. *Innovations in Education and Teaching International*, *57*(5), 577–589. https://doi.org/10.1080/14703297.2019.1585904

Unal, E., & Uzun, A. (2021). Understanding university students' behavioural intention to use Edmodo through the lens of an extended technology acceptance model. *British Journal of Educational Technology*, *52*(2), 619–637. https://doi.org/10.1111/bjet.13046

Venkatesh, V., & Bala, H. (2008). Technology acceptance model 3 and a research agenda on interventions. *Decision Sciences*, *39*(2), 273–315. https://doi.org/10.1111/j.1540-5915.2008.00192.x

Venkatesh, V., & Davis, F. (1996). A model of the antecedents of perceived ease of use: Development and test. *Decision Sciences, 27*(3), 451–481. https://doi.org/10.1111/j.1540-5915.1996.tb00860.x

Venkatesh, V., Morris, M.G., Davis, G.B., & Davis, F.D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425–478. https://doi.org/10.2307/30036540

Wang, C., Wang, W., & Wu, H. (2020). Association between medical students' prior experiences and perceptions of formal online education developed in response to COVID-19: A cross-sectional study in China. *BMJ Open*, *10*, Article e041886. https://doi.org/10.1136/bmjopen-2020-041886

Wang, W. (2021). Medical education in China: Progress in the past 70 years and a vision for the future. *BMC Medical Education*, *21*(1), 1–6. https://doi.org/10.1186/s12909-021-02875-6

Yan, L., Whitelock-Wainwright, A., Guan, Q., Wen, G., Gašević, D., & Chen, G. (2021). Students' experience of online learning during the COVID-19 pandemic: A province-wide survey study. *British Journal of Educational Technology, 52*, 2038–2057. https://doi.org/10.1111/bjet.13102

Zhao, Y., Wang, N., Li, Y., Zhou, R., & Li, S. (2021). Do cultural differences affect users' e-learning adoption? A meta-analysis. *British Journal of Educational Technology*, *52*(1), 20–41. https://doi.org/10.1111/bjet.13002

Zhu, Y., Geng, G., Disney, L., & Pan, Z. (2023). Changes in university students' behavioural intention to learn online throughout the COVID-19: Insights for online teaching in the post-pandemic era. *Education and Information Technologies*, *28*, 3859–3892. https://doi.org/10.1007/s10639-022-11320-0

Corresponding author: Feifei Han, feifei.han@acu.edu.au

Please cite as: Han, F. (2024). Factors affecting Chinese undergraduate medical students' behavioural intention and actual use of intelligent tutoring systems. *Australasian Journal of Educational Technology*, *40*(2), 76–93. https://doi.org/10.14742/ajet.8814