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Application and effectiveness of blended learning in medical imaging via the technology acceptance model

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Abstract

Blended learning, which integrates online education with face-to-face instruction, is becoming an increasingly vital component of higher education. While there is an extensive research on blended learning, studies specifically examining student perceptions in the field of medical imaging are limited. This study investigates the satisfaction and behavioral intentions of students enrolled in a blended "Medical Imaging" course at Hainan Medical University. We employed a quantitative research approach, using a modified Technology Acceptance Model (TAM) questionnaire to fit the specific context of blended learning. Data were collected from 145 valid responses and analyzed using SPSS 26 and Smart-PLS 3.3.3. The findings reveal that blended learning positively impacts student satisfaction and engagement, underscoring its value in higher education. Additionally, the study supports the integration of the TAM to enhance the effectiveness of blended learning for students.

Keywords Blended learning, Technology Acceptance Model (TAM), Student behavioral intention, Higher education technology, Medical imaging

Introduction

As digital technology reshapes our methods of teaching and learning, the educational landscape is undergoing a rapid transformation. Given the potential of online training and mobile learning to meet the evolving needs of tech-savvy student populations, traditional teaching methods are being re-evaluated [1]. Blended learning, which combines digital and face-to-face instruction, has gained widespread attention as a promising educational model [2–4]. Medical imaging education involves not only the transmission of theoretical knowledge but also emphasizes the development of practical and hands-on skills [5]. Within this educational context, the discipline of medical imaging is faced with ever-increasing teaching demands, particularly the challenge of effectively integrating theoretical knowledge with practical skills. Students in this field often need to use specialized equipment and engage in clinical simulations to master complex imaging techniques and operational procedures. The blended learning model can offer a flexible approach by integrating online learning with hands-on practice. For instance, students can learn the theoretical aspects of imaging principles and equipment operation online, and then perform practical tasks in a laboratory or clinical setting. This combination not only enhances learning efficiency but also boosts students' confidence and practical abilities. Additionally, the advent of virtual reality (VR) and augmented reality (AR) technologies has opened new avenues for creating interactive and immersive learning

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experiences [6]. This approach holds significant potential to improve teaching outcomes and cater to the evolving needs of students [6]. Therefore, adopting blended teaching methods will become an essential auxiliary tool in medical imaging education practices [7–13].

However, the user's experience and satisfaction of medical imaging students with blended learning have not been accurately assessed, and the effectiveness of blended learning among students needs evaluation. This study represents the first application of the Technology Acceptance Model (TAM) in the field of medical imaging education, aimed at dissecting the unique relationship between technology acceptance and the specific competencies that medical imaging students must acquire. By analyzing students' acceptance of blended learning, we investigate how to enhance teaching effectiveness through technology. This has significant practical implications for current and future medical imaging educators, as it can assist them in better designing and implementing educational strategies. This study also seeks to elucidate the advantages and limitations of this educational model in this demanding field. Our investigation revolves around two key questions:

How do personal factors, such as technological proficiency and individual learning preferences, influence medical imaging students' acceptance of blended learning?

What role do external factors, such as institutional support and resource availability, play in this acceptance process?

By constructing a new conceptual model and conducting confirmatory factor analysis, we aim to provide nuanced insights into medical imaging students' perceptions and interactions with the blended learning model. Our research seeks to bridge the gap between empirical evidence and practical application, guiding educators in integrating technological advancements into medical imaging education. We hope this study will highlight the unique potential of blended learning to enrich the tactile and cognitive dimensions of training proficient professionals in the field of medical imaging.

Theoretical framework and model development

Theoretical review: reasons for choosing the TAM

This study adopts the TAM to assess the effectiveness of the blended learning model. The reasons for selecting the TAM are as follows: (1) Wide Applicability: The TAM has been validated in various educational fields, demonstrating its ability to effectively predict students' acceptance of new technologies [14]. Abuhassna conducted a bibliometric and content analysis of the usage trends of TAM, further confirming the applicability and significance of this model within the continuously evolving field of educational technology [15]. (2) Flexibility: TAM exhibits a high degree of flexibility, allowing it to be adjusted according to specific educational contexts to meet different learning needs and backgrounds [14, 16]. This adaptability enables us to effectively apply the model in medical imaging education and make necessary extensions. (3) Empirical Support: A substantial body of empirical research indicates that perceived ease of use (PEU) and perceived usefulness (PU) significantly influence users' behavioral intentions, providing a solid theoretical foundation for this study [14–17]. These factors have been shown to be crucial in affecting technology acceptance across various contexts. By selecting and expanding the TAM, this study aims to explore in-depth the acceptance of blended learning among medical imaging students and its related influencing factors.

Although TAM has been widely applied in numerous educational studies, its application in medical imaging education requires a stronger theoretical foundation. Medical imaging education has its unique requirements, including the use of high-tech equipment, complex image analysis skills, and a close integration with clinical practice. Therefore, understanding the relationships between TAM constructs and their relevance to the unique demands of medical imaging education is crucial.This study employs descriptive and explanatory quantitative research methods aimed at assessing the effectiveness of a blended learning approach through statistical analysis.

Key factors

This study employs the TAM to evaluate the impact of the blended learning model on student satisfaction and behavioral intention. To achieve this, it is essential to identify several key factors that will play a crucial role in the subsequent model hypotheses and development. To ensure effective instructional design, Abuhassna [15] and Alnawajha [18] emphasized the importance of integrating TAM with principles of instructional design. They proposed an easily understandable and implementable framework, which offers a valuable perspective for our research.

(1) Personal influence factors (PIFs)

PIFs, including individual innovation ability, learning style, and learning desire, significantly affect blended learning. Individual innovation ability is vital for the success of blended learning; students with strong innovation abilities are more likely to embrace new technologies [19, 20]. Different learning styles also shape attitudes toward blended learning; for instance, students who prefer independent learning may lean towards online resources [21, 22].

Moreover, a strong desire to learn through diverse methods enhances engagement and outcomes in a blended environment [23].

(2) External influence factors (EIFs)

EIFs, such as environmental pressure, direct experience with technology, and technological infrastructure, greatly impact blended learning usage [23–27]. Environmental pressure, including social influences, can motivate individuals to adopt blended learning when they perceive endorsement from peers or educators. Positive direct experiences with technology, supported by adequate training, foster a willingness to engage with blended resources [25]. Lastly, robust technological infrastructure is essential for the successful implementation of blended learning, affecting both its effectiveness and student engagement [26, 27].

(3) Perceived Ease of Use (PEU)

PEU refers to how easily users can understand and operate a system [26]. In blended learning for medical imaging, students face complex imaging software and equipment. High PEU means that these technological tools should be designed to be easy to operate and understand, thereby reducing technological barriers for students and allowing them to focus on learning the core content [28]. Conversely, if the system is perceived as difficult to navigate, students may develop negative feelings, reducing their engagement. A user-friendly system enhances access to resources and communication within the learning platform, thus improving overall satisfaction [29, 30].

(4) Perceived usefulness (PU)

PU reflects an individual's belief regarding the benefits of using a particular technology for efficiency [31]. Medical imaging education involves a substantial amount of image analysis and diagnostic tasks. Therefore, students need to believe that the technology they use can significantly enhance their learning and practical efficiency. When students find that these technological tools help them better understand and analyze medical images, they are more inclined to accept and utilize these tools. This will directly impact their learning outcomes and career preparedness [32, 33].

(5) Student Satisfaction (SS)

SS in blended learning pertains to how well the model meets students' expectations and needs [32–34]. It encompasses contentment with learning resources and interactions, serving as a critical measure of blended learning's effectiveness [35–38]. Understanding SS allows educators to adjust strategies to enhance learning experiences and outcomes [39], while also serving as a metric for decision-makers evaluating blended learning initiatives [40].

(6) Behavioral Intention (BI)

BI in blended learning indicates students' willingness to use specific technologies [41]. It reflects their attitudes toward engagement with these tools [40]. Positive perceptions of ease of use and usefulness lead to favorable BI, facilitating better learning outcomes [41–44]. Promoting BI is crucial for effective blended learning implementation.

Hypotheses and model development

Based on the key factors identified above, we propose the following seven hypotheses to explore how these factors interact and ultimately influence student satisfaction and behavioral intention.

H1: Personal influence factors have a positive effect on perceived ease of use.

Previous studies have shown that an individual's innovativeness is positively correlated with technology acceptance [19, 20]. Students with higher levels of innovation are more likely to perceive technology as easy to use.

H2: Personal influence factors have a positive effect on perceived usefulness.

Research indicates that an individual's learning motivation and learning style directly impact their perception of usefulness [21, 22].

H3: External influence factors have a positive effect on perceived ease of use.

Prior studies have pointed out that social support and environmental pressures can significantly enhance users' perceptions of the ease of use of new technologies [25].

H4: External influence factors have a positive effect on perceived usefulness.

Previous research suggests that the level of technological infrastructure directly affects students' perceptions of the usefulness of technology [26, 27].

H5: Perceived ease of use has a positive effect on student satisfaction.

Studies indicate that when users find a system easy to use, they are more likely to develop a positive attitude toward it, thereby increasing their satisfaction [29, 30].

H6: Perceived usefulness has a positive effect on student satisfaction.

Research has shown that perceived usefulness significantly influences user satisfaction [32, 33].

H7: Student satisfaction has a positive effect on students' intention to use.

Previous studie have highlighted that students' satisfaction with the learning process is closely related to their future intention to use the technologys [41–44].

Conceptual model diagram

Figure 1 illustrates the conceptual model of this study, clearly depicting the relationships among PIFs, EIFs, PEU, PU, SS, and BI. The design of the model aims to explore how these variables interact and influence students' learning experiences and BI in medical imaging education.

Research methodology

This study employs a blended learning model as its foundation, integrating the TAM for analysis. The aim is to gain deeper insights into medical imaging students' perceptions and usage of the blended learning approach, thereby providing more systematic insights for educational practice. The research design is divided into three main stages:

Questionnaire design

The development process of the questionnaire involved the following steps:

(1) Feedback from Longitudinal Blended Learning Reforms: The questionnaire was developed based on iterative feedback obtained from the cohort of students enrolled between 2019 and 2021 (Class of 2019–2021) during our blended learning reform. During this period, we collected end-of-semester student surveys (n=130). Although these surveys were not explicitly structured around the Technology Acceptance Model (TAM), they provided critical insights into key pain points, such as student satisfaction with online teaching platforms, the effectiveness of blended teaching methods in enhancing understanding of clinical cases, and suggestions for improvement. These historical data are archived in Supplementary File 1.

(2) Literature Review: Based on prior research, key variables were identified, and related questions were designed. Figure 1 illustrates the model we established, which consists of six components: PIF, EIF, PEU, PU, SS, and BI. Seven pathways were proposed between these six components, hypothesizing relationships among different variables [45], thus providing a theoretical foundation for subsequent empirical analysis. Each hypothesis aims to predict the interactions among these six constructs. For each component, three specific questions were designed to ensure comprehensive coverage of various aspects of the variables. The questionnaire utilized a five-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree), facilitating the quantification of SS and BI regarding blended learning [46, 47]. The TAM-based survey questionnaire is detailed in Table 1, with the complete original survey available in Supplementary File 2.

(3) Expert Review: Experts in the fields of education and psychology were invited to review the questionnaire to ensure the validity and applicability of the questions. Including one medical imaging professor with over 20 years of teaching and research experience, who is also an advocate for blended learning in the field. A psychology professor specializing in educational psychology and questionnaire design. A statistics professor specializing in data analysis and survey research methods. Feed-

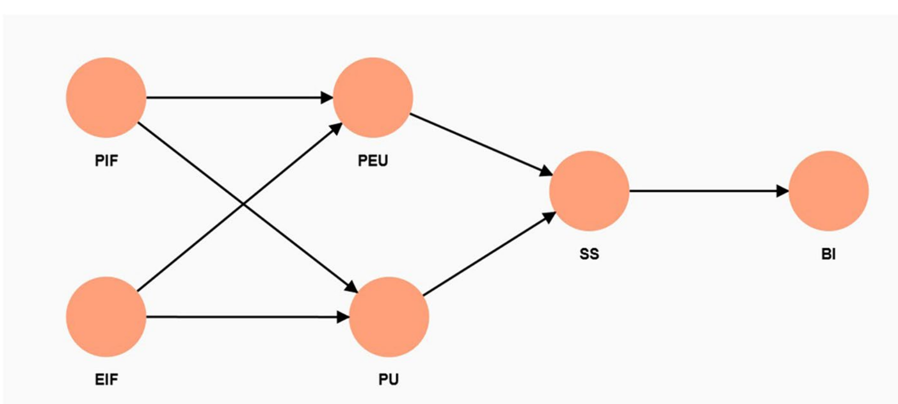

Fig. 1 Conceptual Model of the Study. PIF = Personal Influence Factor, EIF = External influence factors, PEU = Perceived Ease of Use, PU = Perceived Usefulness, SS = Student Satisfaction, BI = Behavioral Intention, H1 ~ H7 represent Hypotheses 1 to 7

Table 1 Questionnaire design based on the TAM

Question Design			Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
Perceived Usefulness (PU)	PEU 1	The content of blended learning is rich and practical.					
	PEU 2	Blended learning can improve learning efficiency.					
	PEU 3	Blended learning can enhance learning interest.					
Perceived Ease of Use (PEU)	PU 1	Blended learning makes it easier to find the necessary learning resources.					
	PU 2	Blended learning facilitates communication and interaction with teachers and classmates.					
	PU 3	Blended learning can improve learning effectiveness.					
Personal influence factors (PIFs)	PIF 1	You are more willing to use new technologies and methods in daily learning.					
	PIF 2	You prefer independent learning over collaborative learning.					
	PIF 3	You hope to better grasp knowledge through different learning methods.					
External influence factors (EIFs)	EIF 1	School leaders and teachers encourage the use of blended learning.					
	EIF 2	You have participated in blended learning training and received technical support provided by the school.					
	EIF 3	You believe that the technological infrastructure provided by the school makes blended learning easier to implement.					
Student Satisfaction (SS)	SS 1	Blended learning improves learning effectiveness, increases learning enjoyment, and enhances learning motivation.					
	SS 2	Blended learning can enhance learning experience and efficiency.					
	SS 3	Blended learning provides sufficient technical support to help you solve problems encountered in learning.					
Behavioral Intention (BI)	BI 1	You are willing to continue using this teaching method in the future.					
	BI 2	You are willing to actively participate in learning in blended learning.					
	BI 3	You are willing to recommend the blended learning model to others.					

back from these experts was used to modify and optimize the content of the questionnaire, ensuring its scientific rigor and appropriateness.

Questionnaire collection

Data were collected from university students through a survey method, targeting undergraduate students majoring in Medical Imaging and Clinical Medicine at Hainan Medical University.

Questionnaire distribution

The questionnaire link was sent to the target student population via an online platform, ensuring anonymity to improve response rates. Promotion was carried out through social media and school announcements to enhance participation.

Data screening

Returned questionnaires were screened to eliminate incomplete or invalid responses, resulting in a final count of 145 valid questionnaires. The criteria for data screening included completeness, logical consistency, and response time to ensure data quality [48, 49].

Data analysis

The collected data were analyzed using Smart PLS 3.3.3 and IBM SPSS 26 software [50]. SPSS was used for descriptive statistical analysis to understand the basic characteristics of the data. Smart PLS (Partial Least Squares) is a widely used statistical tool in social sciences, particularly suitable for constructing and evaluating structural equation models. The primary purpose of using Smart PLS in this study is to analyze the complex relationships between latent variables and explore the key factors influencing medical imaging students' acceptance of blended learning. The specific steps are as follows: first, import the data and create a new project, then draw the path model, set latent variables and measurement indicators, and establish hypothesized causal paths. Run the PLS algorithm, configure options, and generate statistical values such as path coefficients, loadings, and effect sizes. Finally, interpret the results, including reliability and validity assessment, internal consistency reliability (ICR), and path coefficients. This process ensures the accuracy of the analysis and the reliability of the results, providing robust data support for the research.

Specific evaluation indicators include: ①Validity Testing: In the structural equation model, we both convergent validity and discriminant validity to assess data validity. Convergent validity was measured using the Average Variance Extract (AVE) formula, with an AVE value greater than 0.5 indicating satisfactory convergent validity [51, 52]. Discriminant validity was assessed using the Fornell-Larcker criterion, cross-loading analysis, and the Heterotrait-Monotrait Ratio (HTMT) [51, 52]. ②Reliability Assessment: ICR is an important indicator of data reliability, evaluated using Composite Reliability (CR) and Cronbach's Alpha (CA). Both CA and CR values exceeding 0.7 indicate satisfactory reliability [51, 52]. ③Model Evaluation: The model was evaluated by examining the path coefficients (PC), *t*-values, and *P*-values to test the significance of relationships within the structural equation model [51, 52]. A significance level of $P < 0.05$ was set to determine the extent of support for the hypotheses.

Results

Demographic information

A total of 256 questionnaires were distributed in this study, resulting in 145 valid responses (a valid response rate of 56.6%). The basic information of the participants is as follows: 57 males (39.3%) and 88 females (60.7%). All participants were aged between 18 and 25 years. The enrollment years of the participants ranged from 2018 to 2022, encompassing undergraduate students from various academic levels, with detailed information provided in Table 2. The majority of responses, 134, came from Medical Imaging students, with only 11 from Clinical Medicine due to the earlier adoption of blended learning in Medical Imaging since 2018. Despite the uneven distribution, both majors are pertinent to our study, ensuring relevance. Our analysis, unweighted by major, draws from the collective feedback, indicative of overall trends. This demographic information lays a foundation for subsequent data analysis, ensuring the representativeness and diversity of the sample.

Table 2 Demographic characteristics

Category	Number	Percentage (%)
Gender		
Male	57	39.31
Female	88	60.69
Age		
18–19	35	24.14
20–21	35	24.14
22–23	57	39.31
23–25	18	12.41
Enrollment years		
2018	47	32.41
2019	26	17.93
2020	19	13.10
2021	15	10.34
2022	38	26.21
Major		
Medical Imaging	134	92.41
Clinical Medicine	11	7.59

Loadings of reflective indicators

Confirmatory factor analysis was conducted through structural equation modeling. Items with standardized factor loadings that were low for measurement variables and latent variables were removed [53]. The standardized factor loadings for all observed variables were greater than 0.7, indicating good reliability [53, 54]. Except for PIF2, which had a loading of 0.470, all other indicators had loadings greater than 0.7, see Table 3, Fig. 2. A total of 17 indicators were included in the analysis.

Internal consistency reliability

Table 4 lists the CA and CR values for all constructs, which are all greater than 0.7, indicating good internal consistency [53]. The specific values are as follows: PIF: CA =0.810, CR =0.818; EIF: CA =0.857, CR =0.865; PEU: CA =0.928, CR =0.932; PU: CA =0.942, CR =0.943; SS: CA =0.962, CR =0.963; BI: CA =0.925, CR =0.934. These results indicate that the internal consistency of all constructs is within an acceptable range.

Convergent validity test

The AVE values for all constructs are greater than 0.5, further supporting the convergent validity of the

Table 3 Loadings of reflective indicators

	BI	EIF	PEU	PIF	PU	SS
BI1	0.954					
BI2	0.949					
BI3	0.893					
EIF1		0.880				
EIF2		0.863				
EIF3		0.902				
PEU1			0.915			
PEU2			0.945			
PEU3			0.945			
PIF1				0.905		
PIF2				0.470		
PIF3				0.891		
PU1					0.940	
PU2					0.960	
PU3					0.939	
SS1						0.955
SS2						0.976
SS3						0.963

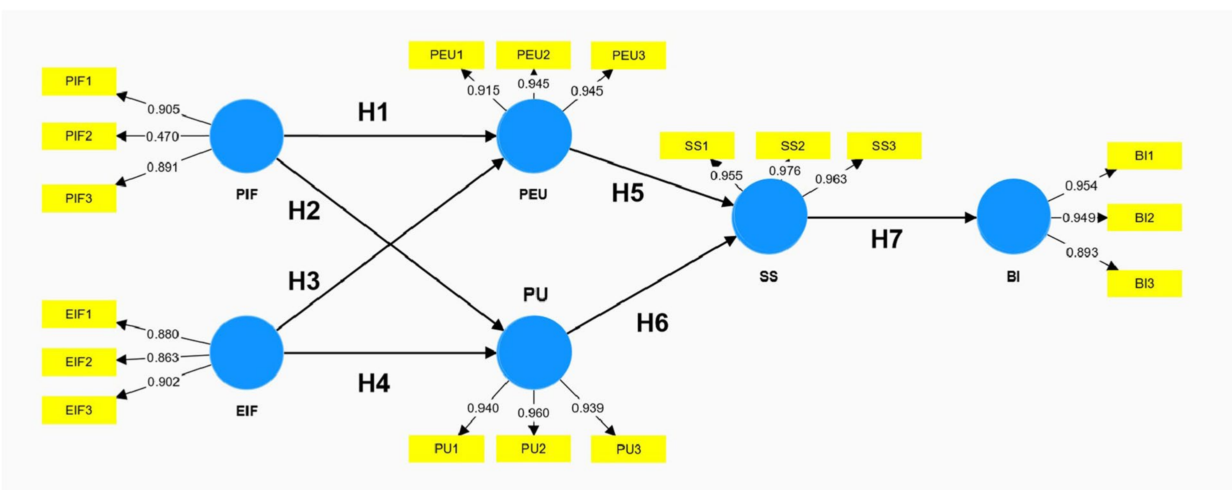

Fig. 2 Schematic Diagram of Indicator Loadings for Each Structure. The numbers on the thin arrows represent the indicator loadings. Except for PIF2, which has a loading of 0.470, all other indicators have loadings greater than 0.7. PIF = Personal Influence Factor, EIF = External influence factors, PEU = Perceived Ease of Use, PU = Perceived Usefulness, SS = Student Satisfaction, BI = Behavioral Intention, H1 ~ H7 represent Hypotheses 1 to 7

model. The specific AVE values are as follows: PIF: AVE = 0.840; EIF: AVE = 0.777; PEU: AVE = 0.875; PU: AVE = 0.896; SS: AVE = 0.930; BI: AVE = 0.869. As shown in Table 4, these results confirm the convergent validity of each construct, indicating that the measured indicators effectively reflect their corresponding latent variables.

Table 4 Summary of reliability and validity indicators

Constructs	Indicators	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
BI	BI 1—BI 3	0.925	0.934	0.952	0.869
EIF	EIF 1—EIF 3	0.857	0.865	0.913	0.777
PEU	PEU 1—PEU 3	0.928	0.932	0.954	0.875
PIF	PIF 1, PIF 3	0.810	0.818	0.913	0.840
PU	PU 1—PU 3	0.942	0.943	0.963	0.896
SS	SS 1—SS 3	0.962	0.963	0.976	0.930

Discriminant validity test

In this section, we will evaluate the discriminant validity of the latent constructs using the Fornell-Larcker criterion, cross-loadings analysis, and the HTMT [51, 55].

According to the Fornell-Larcker criterion, to determine whether two latent constructs have discriminant validity, the following conditions must be met: (1) the AVE value of each latent construct must be greater than the square of its correlation coefficients with other constructs; (2) the AVE value of a latent construct must be greater than its cross-loadings with other constructs. The Fornell-Larcker correlation matrix among the variables is shown in Table 5. The analysis indicates that the AVE values of all latent constructs are greater than the square of their correlation coefficients with other constructs, demonstrating good discriminant validity among the latent constructs.

Additionally, discriminant validity can be assessed by calculating the cross-loadings [56, 57]. This involves correlating each item with its respective latent variable and other latent variables to evaluate the relationships between the item and other latent variables. If an item's correlation with its latent variable is significantly greater than its correlations with other latent variables, it is considered to have good discriminant validity. Table 6 summarizes the results of the cross-loadings analysis. All measurement items show significantly higher correlations with their corresponding latent constructs than with other constructs, indicating that all items possess good discriminant validity.

HTMT is another method for assessing the discriminant validity of latent constructs. Generally, HTMT values should be below 0.85 (sometimes acceptable up to 0.90) to ensure sufficient distinction between latent constructs [55]. Table 7 presents the calculated results of the HTMT matrix. From the HTMT analysis, the HTMT value between BI and SS is 0.908, which is close to the critical value. The HTMT values between other latent constructs are all below 0.90, indicating good discriminant validity among them.

In summary, through the Fornell-Larcker criterion, cross-loadings analysis, and HTMT evaluation, the latent constructs in this study demonstrate good discriminant validity in most cases. However, the HTMT value between BI and SS being close to 0.90 suggests that there may be some degree of overlap between these two constructs.

Structural model and collinearity

As part of the evaluation, the predictive ability of the structural model was tested. Collinearity refers to a high correlation among independent variables, which can lead to unreliable results in regression analysis. To assess collinearity, we used the Variance Inflation Factor (VIF) values. According to the relevant literature, a VIF value greater than 5 is generally considered indicative of multicollinearity issues [55, 57–59]. However, recent research suggests that a more appropriate threshold should be

Table 5 Fornell–Larcker correlation matrix

	BI	EIF	PEU	PIF	PU	SS
BI	0.932					
EIF	0.838	0.882				
PEU	0.835	0.732	0.935			
PIF	0.756	0.724	0.726	0.917		
PU	0.869	0.710	0.874	0.685	0.946	
SS	0.937	0.833	0.840	0.708	0.850	0.964

Table 6 Summary of cross-loadings matrix

	BI	EIF	PEU	PIF	PU	SS
BI1	0.954	0.775	0.797	0.681	0.809	0.899
BI2	0.949	0.811	0.782	0.676	0.827	0.933
BI3	0.893	0.759	0.757	0.770	0.796	0.776
EIF1	0.776	0.880	0.707	0.738	0.657	0.729
EIF2	0.686	0.863	0.532	0.605	0.579	0.672
EIF3	0.748	0.902	0.680	0.566	0.636	0.795
PEU1	0.734	0.615	0.915	0.624	0.785	0.749
PEU2	0.801	0.728	0.945	0.701	0.843	0.802
PEU3	0.804	0.706	0.945	0.709	0.822	0.804
PIF1	0.712	0.668	0.681	0.926	0.684	0.656
PIF3	0.671	0.660	0.650	0.907	0.566	0.643
PU1	0.799	0.644	0.782	0.659	0.940	0.751
PU2	0.843	0.689	0.830	0.652	0.960	0.837
PU3	0.823	0.683	0.867	0.635	0.939	0.824
SS1	0.876	0.812	0.772	0.653	0.801	0.955
SS2	0.905	0.792	0.832	0.714	0.834	0.976
SS3	0.928	0.807	0.825	0.681	0.825	0.963

Table 7 Heterotrait-monotrait ratio (HTMT) matrix

	BI	EIF	PEU	PIF	PU	SS
BI						
EIF	0.841					
PEU	0.882	0.811				
PIF	0.878	0.866	0.835			
PU	0.823	0.787	0.843	0.781		
SS	0.908	0.834	0.887	0.801	0.802	

Table 8 Variance inflation factor (VIF)

	BI	EIF	PEU	PIF	PU	SS
BI						
EIF			2.105		2.105	
PEU						4.232
PIF			2.105		2.105	
PU						4.232
SS	1.000					

less than or equal to 3.3 [56, 60]. This stricter standard aids in more accurately identifying potential collinearity problems. In this study, we calculated the VIF values for each latent construct, which are listed in Table 8. According to the data in Table 8, all constructs have VIF values below 5, indicating that there are no severe multicollinearity issues. The VIF values for PEU-SS and PU-SS are 4.232, which, while not exceeding the threshold of 5, approaches the limit of 3.3, suggesting that further attention may be needed regarding the relationship between these two constructs. The VIF value for EIF and PIF is 2.105, indicating a low risk of collinearity. The VIF value for SS is 1.000, showing that this construct has no collinearity issues with other constructs.

Table 9 Model hypothesis testing

Path of Hypotheses	PC	Standard deviation (STDEV)	95%CI	Effect Size (f^2)	*t*-values (STDEV)	*P*-values	Results
SS → BI	0.937	0.014	0.90956,0.96444	7.144	68.891	< 0.001	Supported
EIF → PEU	0.434	0.105	0.2275,0.6405	0.234	4.132	< 0.001	Supported
EIF → PU	0.450	0.112	0.2314,0.6686	0.222	4.028	< 0.001	Supported
PEU → SS	0.410	0.15	0.1158,0.7042	0.168	2.737	0.006	Supported
PIF → PEU	0.412	0.113	0.1927,0.6313	0.211	3.659	< 0.001	Supported
PIF → PU	0.359	0.102	0.1576,0.5604	0.141	3.506	< 0.001	Supported
PU → SS	0.492	0.147	0.2054,0.7786	0.241	3.338	0.001	Supported

PC Path coefficients, *CI* confidence interval, *PIF* Personal influence factor, *EIF* External influence factors, *PEU* Perceived Ease of Use, *PU* Perceived usefulness, *SS* Student Satisfaction, *BI* Behavioral Intention

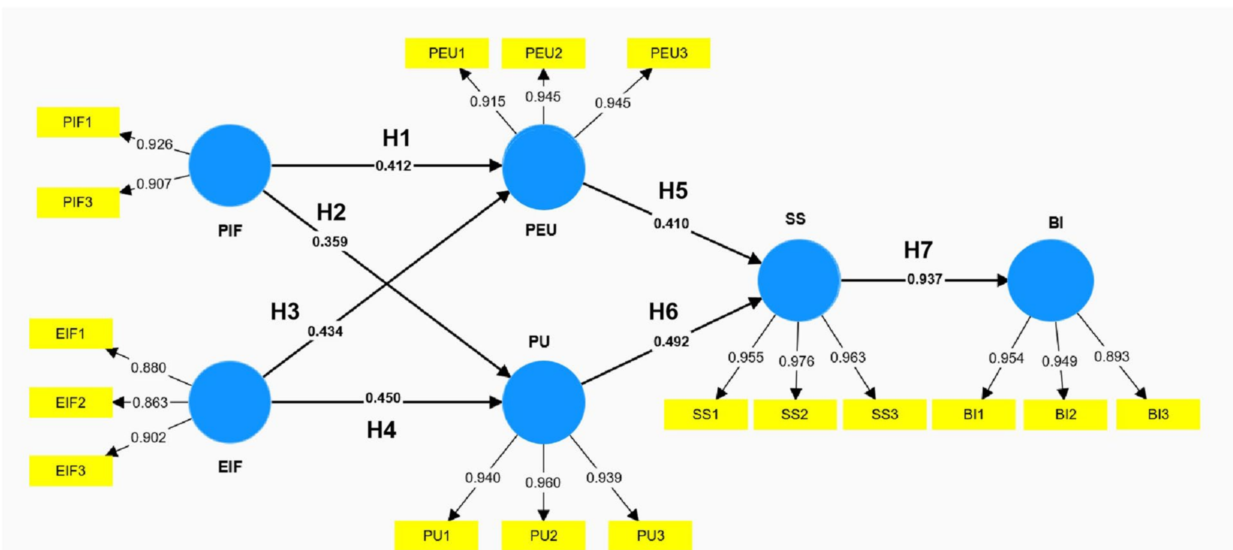

Fig. 3 Structural Model Hypothesis Testing. The numbers on the thin arrows represent the indicator loadings, while the numbers on the thick arrows represent the path coefficients. PIF = Personal Influence Factor, EIF = External influence factors, PEU = Perceived Ease of Use, PU = Perceived Usefulness, SS = Student Satisfaction, BI = Behavioral Intention, H1 ~ H7 represent Hypotheses 1 to 7

Structural model hypothesis testing

Table 9 and Fig. 3 present the bootstrap results for all structures. Generally, an absolute value greater than 0.3 is considered to have a significant impact, while an absolute value greater than 0.5 is considered to have a substantial impact [57, 59]. For the relationship PIF → PEU (PC = 0.412; t = 3.659; P < 0.001), the corresponding hypothesis (H1) is supported. For PIF → PU (PC = 0.359; t = 3.506; P < 0.001), the corresponding hypothesis (H2) is also supported. Regarding hypotheses H3 and H4, both EIF → PEU (PC = 0.434; t = 4.132; P < 0.001) and EIF → PU (PC = 0.450; t = 4.028; P < 0.001) provide support for the respective hypotheses. There are significant impacts between PEU → SS (PC = 0.410; t = 2.737; P = 0.006) and PU → SS (PC = 0.492; t = 3.338; P = 0.001); thus, the corresponding hypotheses (H5, H6) are supported. The relationship SS → BI (PC = 0.937; t = 68.891; P < 0.001) indicates support for the corresponding hypothesis (H7).

Discussion

Blended learning has been applied in various disciplines, and multiple studies have shown that integrating online teaching models can enhance both student performance and satisfaction [61, 62]. This study aims to explore the satisfaction and behavioral intentions of students regarding blended learning in the "Medical Imaging" blended course at Hainan Medical University, based on the TAM for empirical analysis. By collecting and analyzing 145 valid questionnaires, we found that blended learning has a positive and constructive impact on medical imaging education. Through well-designed online and offline teaching activities, it can effectively promote students' familiarity with and mastery of medical imaging equipment techniques. This not only cultivates students' practical skills but also deepens their understanding of theoretical knowledge. These findings are crucial for medical imaging educators, providing them with valuable guidance on how to utilize modern technology to improve teaching methods in order to meet the increasingly complex instructional demands of the medical imaging field.

Student acceptance of blended learning

Path coefficient analysis shows that SS has a highly significant effect on BI (PC =0.937), indicating that satisfaction plays a dominant role in forming user BI. This finding emphasizes the importance of enhancing SS in the design of educational models [63, 64]. Meeting students' expectations for learning experiences can directly translate into higher engagement willingness, thereby promoting their learning motivation and outcomes.

PIFs, such as learning motivation and learning styles, also play an important role in this process. Students with a higher tendency for self-directed learning are often more willing to accept blended learning because they can actively utilize online resources and learn at their own pace. This learning motivation directly affects their sense of participation and satisfaction. EIFs also play a critical role in this process. The effective dissemination of external information sources can significantly enhance students' PEU and PU of blended learning, thereby improving their satisfaction. Technical support provided by the school and guidance from teachers can help students better understand the advantages of blended learning, reducing their resistance.

Impact of perceived ease of use and perceived usefulness

This study finds that PEU and PU both positively influence SS, specifically, the path coefficient for PEU is 0.410, and for PU it is 0.492. This indicates that the more users perceive the system as easy to use and useful, the higher their satisfaction will be. This finding aligns with the previously proposed TAM theory [65, 66], further validating the importance of users' perceptions of system operability and utility on their usage attitudes.

EIF have a significant impact on PEU and PU, with path coefficients of 0.434 and 0.450 respectively, indicating that students' cognition of information directly influences their usage experience. Therefore, educational institutions should prioritize the effectiveness of information dissemination to ensure that students can access accurate information and support regarding blended learning. Additionally, PIF also significantly affect PEU and PU, with path coefficients of 0.412 and 0.359. Although relatively small, they still show a degree of influence. This may suggest that, aside from individual learning motivations and styles, external information sources may be more crucial in influencing user cognition.

Relationship between student satisfaction and behavioral intention

The research findings indicate that SS has a very high effect size on BI ($f^2 = 7.144$), suggesting that this relationship is extremely significant, meaning that increasing SS will strongly positively influence their BI. All path *P*-values are below 0.05, particularly the *P*-value for SS $\rightarrow$ BI is less than 0.001, further enhancing our confidence in the non-random nature of these relationships. It is emphasized again that while PIFs, such as learning styles and technological proficiency, show some influence in the path coefficients, the dissemination of external information and teacher support may be more significant in affecting students' cognition and acceptance.

Practical implication

These results hold significant practical implications for medical imaging education. Educational institutions can enhance SS and BI by improving PEU and PU. Specifically, educational institutions might consider the following strategies: (1) Schools can introduce VR and AR technologies in a blended learning environment to provide near-real operational experiences. Such technological applications can simulate the actual operational environment of medical imaging, enabling students to practice and master key skills in a risk-free context. (2) To ensure educators can effectively implement blended learning, they need to receive specialized technical training to understand how to use simulation equipment and online platforms for teaching. Additionally, ample resources such as teaching guides, best practice cases, and technical support should be provided to help teachers overcome potential challenges. (3) To foster student engagement and interaction, schools should enhance communication between teachers and students through regular information sessions, expert lectures, and interactive platforms. Ensuring that students have timely access to accurate information and opportunities to provide feedback and ask questions is essential. (4) Continuous improvement of course content: Based on regular satisfaction surveys and feedback collection, educators should continually adjust and refine course content. Implementing incentive mechanisms to encourage active participation and suggestions from students helps cultivate their sense of belonging and ongoing engagement. By integrating the above measures, medical imaging education can move towards a more effective and innovative future. As demonstrated by previous research, the TAM model has been widely applied in assessing the effectiveness of online learning, providing a solid theoretical foundation for choosing TAM as an analytical tool in our study. Furthermore, research by Samsul emphasizes the value of educational big data in evaluating learning patterns and student acceptance [67], further proving the importance of adopting data-driven methods for educational reform. Therefore, our research findings offer concrete, actionable guidance for medical imaging educators and institutions, as well as opening new paths and perspectives for future research on educational technology.

Future research directions

Although the results of this study indicate significant relationships among the paths, future research could further explore potential mediating variables, such as user personality traits and cultural backgrounds, in these relationships. Additionally, validation in different cultural or industry contexts would enhance the model's generalizability. Finally, studying the temporal changes in user satisfaction and BI will help observe whether these relationships remain consistent over time, providing more dynamic guidance for educational practice.

Moreover, it is worth noting that research combining other learning theories is also valuable. For instance, exploring how the Community of Inquiry (CoI) framework and TAM can complement each other provides a richer perspective for understanding students' experiences in a blended learning environment [68, 69]. High levels of social presence can enhance student engagement, thereby increasing their acceptance of blended learning; at the same time, teaching presence, through the support and guidance of educators, can improve students' perceptions of the ease of use and usefulness of learning materials. We also suggest that future research consider adopting systematic review and meta-analysis methodologies. Through this approach, researchers can evaluate a broader range of literature to determine the general effectiveness and key success factors of blended learning across various educational settings. Systematic reviews can help identify and synthesize relevant research findings already conducted in different cultural and educational contexts, while meta-analyses can quantify the differences in results among these studies. This methodology will contribute to further validating the model found in our study and may reveal common factors affecting student acceptance rates, which can provide stronger evidence support for educational policymakers and practitioners.

Limitations

This study has several limitations. (1) Although the TAM questionnaire demonstrated good reliability and validity in our study, we did not conduct a formal pilot test prior to data collection. Future research should incorporate cognitive interviews or small-scale piloting to further refine the instrument for medical imaging education contexts. (2) The questionnaire used in this study was designed based on the generic TAM, thus it has good applicability and generalizability. However, it's acknowledged that there are limitations in the questionnaire regarding its specificity to the unique needs of medical imaging students. For instance, there is a lack of specific inquiry into the access to simulated medical imaging equipment, as well as a targeted evaluation of specialized online resources. In subsequent research, we plan to customize and refine the questionnaire items further, taking into account the particularities of the medical imaging discipline, to ensure more accurately capturing and meeting the educational needs of medical imaging students. (3) The study's single-institution context at Hainan Medical University limits the external validity of the results. Future research should include students from multiple institutions and specialties to enhance generalizability. Additionally, the cross-sectional design only captures data at one point in time, potentially missing changes in long-term acceptance and satisfaction with blended learning. Longitudinal methods should be employed to track attitudes over time. (4) Self-report bias could lead to socially desirable responses rather than true feelings. Future research should combine objective data, such as academic performance and online behavior, with self-reported data for a more accurate assessment. Despite the use of TAM, other factors like teacher support and learning motivation could also impact acceptance and satisfaction. Integrating additional variables could provide a more comprehensive understanding. (5) Structural equation modeling relies heavily on quantitative data, which might not fully capture the complex perceptions students have toward blended learning. Qualitative methods, such as interviews or focus groups, should be utilized in future research for deeper insights. Additionally, the high correlation between PEU-SS and PU-SS in our study, with VIF values nearing the threshold of 3.3, indicates potential multicollinearity that could affect the stability and interpretability of model parameters. While multicollinearity is not severe in the current analysis, it could lead to unreliable estimates for some parameters. Future studies could address and validate these issues by using different data collection methods, increasing sample sizes, or applying alternative statistical techniques.

Conclusion

In summary, this study empirically confirmed the effectiveness of blended learning in medical imaging education. Future educational practices should emphasize the individual differences among students and the influence of external environments, optimizing the design and implementation of blended learning to meet the growing learning needs of students. By continuously improving teaching strategies, higher education institutions can better leverage blended learning models to enhance educational quality and improve students' learning experiences.

Supplementary Information

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Supplementary Material 1.

Supplementary Material 2.

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Human Ethics and Consent to Participate declarations
The ethical aspects of this study have been reviewed and approved by the Biomedical Ethics Committee of the First Affiliated Hospital of Hainan Medical University, and informed consent was obtained from all individual participants involved in the study.

Authors' contributions
Xiaofen Sun: Conceptualization, Data curation, Formal Analysis, Investigation, Methodology, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. Jianghua Wan: Conceptualization, Data curation, Formal Analysis, Investigation, Software, Supervision, Writing original draft, Writing – review & editing. Zhiqun Li: Formal Analysis, Investigation, Methodology, Validation, Writing – original draft, Writing – review & editing. Rong Tu: Conceptualization, Methodology, Project administration, Supervision, Writing – review & editing. Juan Lin: Conceptualization, Data curation, Investigation, Writing – original draft. Xiaohua Li: Conceptualization, Data curation, Investigation, Methodology, Writing – original draft. Jianqiang Chen: Conceptualization, Data curation, Project administration, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. All authors reviewed the manuscript.

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Data availability
Data is provided within the manuscript and supplementary information files.

Declarations

Ethics approval and consent to participate
This study has been approved by the Biomedical Ethics Committee of the First Affiliated Hospital of Hainan Medical University (Approval No: 2024-KYL-176). To ensure confidentiality, the collection of participants' questionnaires and the related analysis were conducted anonymously. We provided a detailed explanation of the study objectives to all students who participated in the blended learning of medical imaging. Informed consent forms were distributed to all students, and written informed consent was obtained from all participants before their participation in the questionnaire survey. The survey was conducted under conditions that protected the privacy, confidentiality, and anonymity of participant information. Participants voluntarily chose whether or not to participate in the research and were informed of their right to withdraw from the study at any time without penalty.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

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