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Adoption of blended learning: Chinese university students' perspectives

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Against the backdrop of the deep integration of the Internet with learning, blended learning offers the advantages of combining online and face-to-face learning to enrich the learning experience and improve knowledge management. Therefore, the objective of this present study is twofold: a. to fill a gap in the literature regarding the adoption of blended learning in the post-pandemic era and the roles of both the technology acceptance model (TAM) and the theory of planned behavior (TPB) in this context and b. to investigate the factors influencing behavioral intention to adopt blended learning. For that purpose, the research formulates six hypotheses, incorporates them into the proposed conceptual model, and validates them using model-fit indices. Based on data collected from Chinese university students, the predicted model's reliability and validity are evaluated using structural equation modeling (SEM). The results of SEM show that (a) the integrated model based on the TAM and the TPB can explain 67.6% of the variance in Chinese university students' adoption of blended learning; (b) perceived usefulness (PU), perceived ease of use (PEU), and subjective norms (SN) all have positive impacts on learning attitudes (LA); (c) PEU has a positive influence on PU, and SN has a positive influence on perceived behavioral control (PBC); and (d) both PU and LA have a positive influence on the intention to adopt blended learning (IABL). However, PEU, SN, and PBC have little effect on IABL; e. LA mediates the effect of PU on IABL, and PU mediates the effect of PEU on IABL. This study demonstrated that an integrated conceptual framework based on the TAM and the TPB as well as the characteristics of blended learning offers an effective way to understand Chinese university students' adoption of blended learning.

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Introduction

Due to the spread of COVID-19, certain conventional face-to-face teaching methods became inappropriate for the current teaching situation. By July 2020, more than 180 countries had closed their schools due to the outbreak. Worldwide, online learning offerings were also reevaluated to meet the difficulties of the global educational environment (UNESCO, 2020). As a consequence of the hazards that COVID-19 posed to teaching and learning, students were compelled to shift from face-to-face to online learning (Yu et al., 2021), with the majority of courses in China opting for blended learning (Kang et al., 2021). In February 2020, China became the first country to announce the launch of online courses. The question of whether online learning could replace traditional offline education has sparked heated debate in China (Jin et al., 2021). Moreover, the Ministry of Education of China issued an announcement in 2021 claiming that it was essential to accelerate the development of new infrastructure, such as intelligent teaching spaces or campuses, as well as to promote blended learning (Yang et al., 2022). Online learning was adopted in China, reducing the consequences of school shutdowns across the country and slowing the virus's spread. Nevertheless, the government was required to address issues concerning what to educate, how to teach, and how to provide fundamental necessities such as education infrastructure. The Chinese Ministry of Education offered a variety of teaching platforms that allowed students to take online lessons via their laptops, desktop computers, cell phones, etc. (Zhang et al., 2020).

Driven by the rapidly changing digital ecosystem, the design and application of blended teaching modes have become important components of the reform of teaching methods in colleges and universities. Blended learning refers to the organic integration of online and offline learning, which may not only guide and inspire students' learning but also arouse students' enthusiasm and autonomy with respect to learning. In addition, Pulham and Graham (2018) identified the top 20 blended teaching skills. Many elements impact students' reactions when these technologies are utilized in the learning process (Xu et al., 2021). Because the actors involved in educational process change, these frameworks undergo constant alteration. Rapid changes in users' digital abilities and attitudes toward technology can be observed (Lazar et al., 2020).

Since that time, the COVID-19 pandemic has exhibited the ordinary trend of ups and downs. Hence, the pandemic has continued for a long period and thus had a substantial influence on many parts of society, particularly education (Cahapay, 2020). The extensive application of online teaching has led to many problems, such as low satisfaction with the teaching effect, low willingness to continue using this type of teaching, and instructional techniques that must be enhanced. Consequently, when users' expectations are met, their contentment increases (Cheng et al., 2019; Kim, 2010); conversely, if their perceived performance falls short of what they had expected, their satisfaction decreases (Mellikeche et al., 2020). However, Popa et al. (2020) proposed that offline education provides the benefits of real-world experience, ease of engaging in diverse activities, cultural value exchange, and simple management and service, which are absent in online education. As a result, the present model of education is gradually evolving, and the mix of online and offline instruction is leading to a major educational revolution.

The inclusion of technology in face-to-face education has aroused a great deal of interest and has opened up several areas of study over the years. Because of its perceived efficiency in offering flexible, timely, and continual learning, blended learning is currently widely regarded as the most popular and effective instruction mode used in educational institutions. Students must adjust to new blended learning techniques and environments with the assistance of modern technologies (Mo et al., 2022). In Chinese universities, faculty should be encouraged to develop courses based on the features of their local institutions during the post-pandemic phase to decrease the learning costs associated with blended learning and the time required to install e-learning platforms. As a result, the teaching effect of blended learning can be enhanced (Lin et al., 2021).

Blended learning has received significant attention and has been widely recognized as "the new normal" based on several influential studies (Dziuban et al., 2018). These studies have highlighted the numerous advantages associated with blended learning. Students, for example, are expected to manage and complete their studies independently of their teacher and at their own pace, so they must have self-regulation abilities and technological proficiency when utilizing online technology outside of their offline meetings. Moreover, to properly utilize and operate technology in teaching as well as develop and post learning materials to students, instructors must be technologically savvy (e.g., with regard to creating quality online videos). Furthermore, educational institutions must offer both instructors and students essential training and technical help to facilitate the successful use of existing technologies as well as the efficient use of the online component (Rasheed et al., 2020).

As a result, importance has been attached to the task of promoting acceptance of blended learning, which is a significant concern for Chinese university students. Several studies have demonstrated the challenges faced by students, teachers, and educational institutions (Ocak, 2011; Broadbent, 2017; Medina, 2018; Prasad et al., 2018). Nevertheless, these studies have been restricted in terms of their capacity to provide a solution to this problem. Furthermore, while several previous studies have focused on the formulation and application of the blended teaching model based on the teaching cases associated with the course, empirical research on the adoption of blended learning from the standpoint of students and the Chinese scenario has been distinctly lacking. Mustafa and Garcia (2021) found that various information system (IS) theories have been integrated into the technology acceptance model (TAM) to improve our understanding of the intention to adopt online learning. Their results showed that task-technology fit (TTF) theory and the theory of planned behavior (TPB) are popular and successful theories that have been combined with the TAM. The TAM is a widely used theoretical framework in information systems and technology research, which aims to understand and predict how users adopt and accept new technologies (Davis, 1985). On the other hand, the TPB is a social psychological theory predicting human behavior (Ajzen, 1985, 1991; Ajzen and Fishbein, 2000). In addition, the research on which they focused is unusual in that it employed an integrated conceptual adoption framework based on the TAM and the TPB from the perspective of Chinese undergraduates for the first time. This approach was the first systematic attempt to scientifically explore and evaluate the variables of students' acceptance and usage of blended learning (Virani et al., 2020).

In the post-pandemic era, blended learning is still an efficient and flexible mode that Chinese university students can adopt because it enables them to interact more closely, engage in more abundant experiences, and improve their understanding (Blain et al., 2022; Müller and Wulf, 2022; Wu and Luo, 2022; Yang and Ogata, 2022). Blended learning can not only assist students in acquiring the habit of self-study but also shed light on creative ways to overcome problems. After interviewing 48 participants in a semi-structured manner, Fletcher et al. (2022) discovered that blended learning is an ideal tool for learners in a post-COVID future. However, Gómez et al. (2022) claimed that face-to-face interactions should be incorporated into blended learning during the post-COVID-19 era. Furthermore, Callaghan et al. (2022) noted that learners perceived their technology exposure as establishing an atmosphere that can have a long-term influence, which is a cognitive tool for learning. Blended learning is a learner-centered and integrated way for learners to study in both the pre-COVID to post-COVID eras that can be investigated through exploratory survey research. Hence, blended teaching is just as popular in the post-pandemic period as it was during the pandemic. To fill the research gap regarding blended learning in a post-pandemic era, this study expands the integrated theory of the TAM and the TPB.

Based on previous debates and in response to the demand for additional data-driven research on the motivation for blended learning (Deng et al., 2019), the current study aims to address the following two questions:

RQ1. To what extent can an integrated conceptual adoption framework based on the TAM and the TPB explain Chinese university students' adoption of blended learning?

RQ2. What factors influence university students' adoption of blended learning?

This research is intended to contribute to arguments about the adoption of blended learning. This paper intends to construct a conceptual model that explains university students' intention to adopt blended learning (IABL) by integrating the TAM and the TPB and to validate five explanatory variables in this context, including perceived usefulness (PU), perceived ease of use (PEU), learning attitudes (LA), subjective norms (SN) and perceived behavioral control (PBC).

Literature review and research hypotheses

Blended learning. Defined as "a judicious blending of face-to-face learning experiences in the classroom with online activities", blended learning combines face-to-face teaching with technology-mediated teaching (Garrison and Kanuka, 2004; Porter et al., 2014). Since the beginning of the twenty-first century, educational institutions have adopted a variety of approaches that blend online instruction with traditional face-to-face instruction, an approach which is known as blended, flipped, mixed, or inverted learning.

Combining educational resources with online interaction has improved the traditional face-to-face model and the entire online form of instruction. Namely, when implemented correctly, this strategy combines the advantages of both the face-to-face and online learning modes of training (Broadbent, 2017; Darling-Aduana and Heinrich, 2018). Blended learning, for example, decreases barriers between professors and their students in online transactions and enhances interaction (Jusoff and Khodabandelou, 2009). Not only does it provide adaptability, educational depth, and cost-effectiveness (Graham, 2006), it also promotes value interaction and learning participation (Dziuban et al., 2004). Hence, it is beneficial for various types of students (Heinze and Procter, 2004).

Due to the popularity of the "Internet+" education application, the notion of blended teaching has steadily emerged (Bai et al., 2016; Tang et al., 2020; Míguez-Álvarez et al., 2020). Hence, blended learning has been regarded as the third generation of advancement in higher education. Traditional face-to-face education is the first generation, and e-learning education is the second generation (Park et al., 2019; Dang et al., 2016), although it is becoming more common at all educational levels. Blended learning tools can bridge the gap between traditional offline and online learning based on networks. A significant portion of the blended learning curriculum (between 30% and 80%) is delivered online (Bazelais et al., 2018). According to this rationale, the blended educational approach may be regarded as a contemporary technique used to facilitate teaching and learning. Some institutes use flipped classroom arrangements, which combine offline and online instruction (Kasat et al., 2019). This approach is a novel learning paradigm that supplements traditional course teaching with online activities (Benbunan-Fich, 2008). Therefore, for developing countries such as China, blended learning is an acceptable technology because of the issues they face, such as a large number of students, scarce resources, tight budgets, and limited space (Halan, 2005; Virani et al., 2020). Blended learning involves a restructuring of curriculum design that aims to activate students' initiative in participating in online learning (Yin and Yuan, 2021).

According to several studies, incorporating information technology (IT) into the teaching process enhances course access and learning opportunities (Turvey and Pachler, 2020). Compared to traditional teaching, arousing students' interest, fostering their enthusiasm, and inspiring their imagination and self-learning consciousness are all positive effects of blended education (Popa et al., 2020).

Technology acceptance model. The TAM, which was initially proposed by Davis (1985) based on the Theory of Reasoned Action (TRA) developed by Fishbein and Ajzen (1975), is a significant model used to research the variables that influence consumers' acceptance of information system technology. Developed by Davis et al. (1989), the TAM is useful for describing and predicting user behavioral intentions regarding information systems. Venkatesh et al. (2003) claimed that behavioral intention, which has bene widely recognized as an agent of acceptance, is the most direct antecedent of technology use, according to the TAM, and is also a fully validated predictor of actual behavior (Tao et al., 2018). PU and PEU are two beliefs that influence behavioral intention. The extent to which an individual perceives that employing technology can boost their ability to accomplish their tasks is known as PU, and the degree to which they feel that doing so will be labor-free is known as PEU (Davis et al., 1989). PEU also has a significant and beneficial influence on PU. Two important primary views within the TAM, i.e., PU and PEU, were developed by synthesizing self-efficacy theory, expectation theory, etc. In addition, the TAM, which includes behavior intention, attitudes, actual usage, and external variables, can explain or predict factors that impact the use of IT (Straub et al., 1995).

The TAM has proven to be capable of explaining technological acceptance in various situations, including information systems for online banking (Chandio et al., 2017), informatics in health (Tao et al., 2018), apps for social networks (Chen et al., 2019), internet banking services (Patel and Patel, 2018), autonomous vehicles (Zhang et al., 2019), digital technology in education (Scherer et al., 2019), mobile tourism apps (Chen and Tsai, 2019), and self-driving cars (Jászberényi et al., 2022), etc. In MOOCs and other e-learning applications, these models have also been explored and expanded (Agudo-Peregrina et al., 2014; Balaman and Baş, 2021; Fianu et al., 2018; Hsu et al., 2018; Scherer et al., 2019; Šumak et al., 2011; Wang et al., 2020; Wu and Chen, 2017; Yoon, 2016). Furthermore, the TAM has been used in various studies to assess learners' intentions to continue using e-learning systems. Chow et al. (2012) showed that when utilizing well-known online study platforms, PU and PEU can boost learning motivation. Hence, they have positive effects on learning through the platform. Similarly, Abdullah and Ward (2016), Islam (2013), Ali et al. (2013), and Zhou et al. (2021) employed the TAM to investigate the impacts of the online system of learning, indicating that PU and PEU can influence the results. Recently, Bai and Jiang (2022) found that the TAM offers influencing factors that support the use of digital resources according to a meta-analysis of 19 research articles. The TAM is thus a sound and reliable paradigm according to the data. Additionally, Alqahtani et al. (2022) utilized the TAM to investigate students' perceptions of continuing to use online platforms following the outbreak of COVID-19. As a result, the TAM was used as a foundational theory in this study to examine the behavioral intentions associated with blended learning. However, this model focuses on the effect of perceptual traits rather than the influence of social aspects, and its explanatory capacity might be improved. Therefore, empirical research on the intention of university students to adopt blended learning using the TAM remains limited (Al-Azawei et al., 2017). Simultaneously, given the limits of the TAM in terms of interpretation, this study seeks to combine the TAM with the TPB to uncover the influencing mechanism underlying university students' intention to adopt blended learning more effectively.

Theory of planned behavior. According to the theory of planned behavior (TPB) (Ajzen, 1985, 1991; Ajzen and Fishbein, 2000), attitudes influence a particular behavior indirectly because of the relationship between SN and PBC. Given a strong desire to perform a specific task, that task is more likely to be completed. A person's attitudes toward the activity show how much that person appreciates given conduct and whether the person anticipates that behavior will result in the associated consequences and values. The evaluation of one's resources, abilities, and competencies with regard to the relevant action is referred to as PBC. Although behavioral intention mediates the effects of attitudes and SN on a particular behavior (Fishbein, 1979), Ajzen (1985) contended that the influence of PBC on behavior becomes manifest both directly and indirectly via behavioral intention (Knauder and Koschmieder, 2019).

On a metatheoretical level, based on the TRA of Fishbein and Ajzen (1975; 1980), Ajzen (1985) proposed in the TPB that individuals systematically analyze information and behave in terms of their outcomes (benefits). These outcomes have been perceived subjectively as the expectations of others who are significant to the individual in question. The TPB has been objectively validated by several academics across various investigations in contexts such as travel destination (Yuzhanin and Fisher, 2016), academic dishonesty (Hendy and Montargot, 2019), sports participation (St Quinton, 2022), private renting (Li et al., 2022), and waste sorting (Bardus and Massoud, 2022). Zaremohzzabieh et al. (2019) and Ashaduzzaman et al. (2022) conducted a meta-analysis to examine the applicability of the TPB. Several academics have empirically validated the TPB in studies on online learning (Hadadgar, et al., 2016; Chu and Chen, 2016; Sungur-Gül and Ateş, 2021).

Theories of integrated TAM and TPB. This study employs the TAM (Davis et al., 1989) and the TPB (Ajzen, 1991) to evaluate the factors influencing university students' intentions to accept blended learning. The TAM has typically been used by academics to uncover elements impacting customers to adopt the new technology. Based on the TAM, individuals' PU and PEU with respect to the technology influence the attitudes, intentions, and behaviors of customers (Davis et al., 1989). In addition, organizational issues impact the PU and PEU associated with technology (Yousafzai et al., 2007). Blended learning research has shown that certain factors have significant effects on learning success, i.e., PU, LA, SN, PBC, and learning behavior; however, PEU does not have such an impact (Wang et al., 2020).

Nevertheless, one drawback of the TAM is that it ignores the function of SN, which is similarly crucial in assessing the intentions of individuals (Venkatesh and Davis, 2000). Personal expectations from society regarding whether to perform a given action are referred to as SN (Hsiao and Tang, 2014). SN is thus one of the most essential aspects of the TPB. According to the TPB, attitudes, SN, and PBC may explain human behavior (Ajzen, 1991). In terms of PU and PEU, the TAM, on the other hand, highlights the attitudes variable in the TPB (Sun et al., 2013). Furthermore, the SN has a comparable social influence (Thompson et al., 1991). Therefore, acceptance tends to be a mix of technical excellence and user characteristics. With regard to indirect factors, social influences (SI) and facilitating conditions (FC) within the organization also have an impact on acceptance (Menant et al., 2021). Several academics have empirically supported the integration of the TAM with the TPB in various contexts, such as the use of social media for transactions (Hansen et al., 2018), physical activity (Tweneboah-Koduah et al., 2019), drone food delivery services (Choe et al., 2021), telecommuting during the COVID-19 outbreak (Chai et al., 2022), and electric vehicle purchases (Vafaei-Zadeh et al., 2022).

Accordingly, this study integrated the TAM with the TPB. Hence, a new research model for blended learning can be developed to illustrate how PU, PEU, LA, SN, and PBC are crucial elements that can impact learners' intention to adopt blended learning. Figure 1 illustrates the study's framework.

Research hypotheses

Perceived usefulness. Defined as the extent to which students feel that blended learning may increase their study efficiency (Davis et al., 1989), PU is regarded as a predictor of attitudes toward behavioral intention. According to a basic model, PU has a favorable effect on behavioral intention. In addition, it frequently influences willingness as mediated by attitudes (Bazelais et al., 2018; Chen and Lu, 2016; Zhou et al., 2021). The role of PU in behavioral intention has previously been investigated extensively, and the results have shown that PU is a substantial predictor of behavioral intention (Chai et al., 2022; Gao et al., 2019; Jin et al., 2021; Kamal et al., 2020; Menant et al., 2021; Patel and Patel, 2018; Scherer et al., 2019; Sharma, 2019). PU is related to students' perceptions of blended teaching's efficacy in increasing their learning results. Teo and Dai (2022) claimed that blended learning can flexibly organize learning time, foster active learning awareness, and improve teacher-student interaction. Students adopt blended learning if its impact is significant. Instead, refusing the integrated education approach can have a negative effect. Thus, the following hypotheses are proposed:

H1: PU positively influences LA toward blended learning.

H2: PU positively influences IABL.

Perceived ease of use. The extent to which students perceive the task of engaging in blended learning to be physically and cognitively challenging is referred to as PEU. The PEU of an item indicates how well it may be comprehended or used. People prefer to utilize considerably easier items (Davis et al., 1989; Lazar et al., 2020; Sharma, 2019). As noted by Venkatesh et al. (2003), students are highly concerned about the complexity of the combination of online learning and offline discussion involved in the blended learning process. According to Wu and Liu (2013), one primary condition for evaluating perceived utility is PEU. Hence, the more students experience the PEU of blended learning courses, the more eager they are to participate in blended learning, and the simpler it is for them to experience the impacts of blended teaching. As a result, the following hypotheses are proposed in this study:

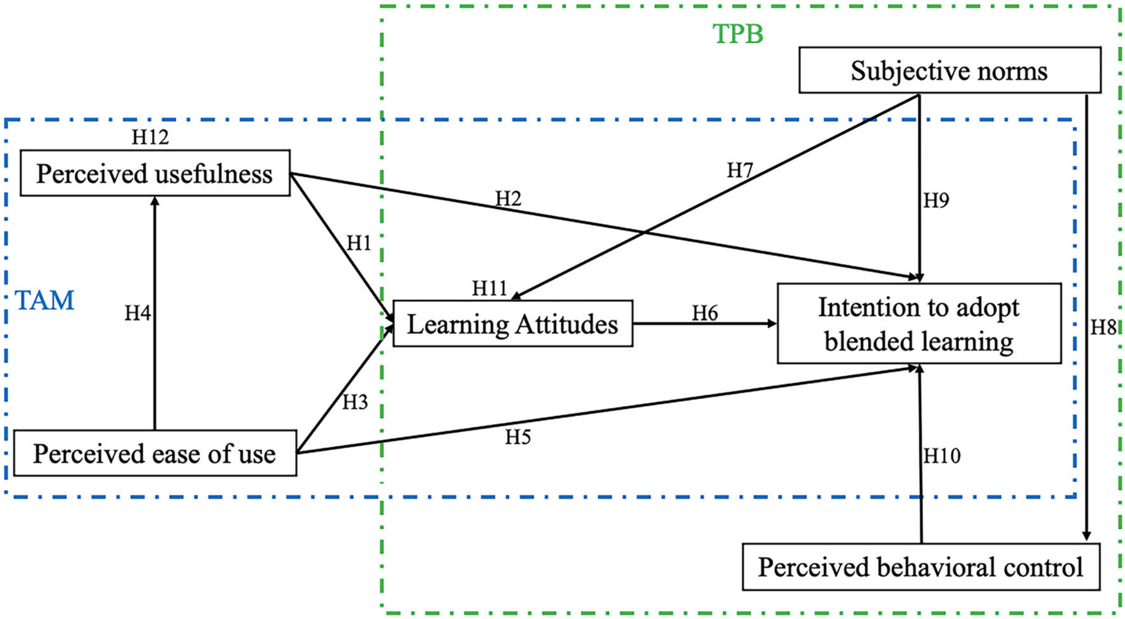

Fig. 1 Research framework. H1–H11 refer to the 11 hypotheses.

H3: PEU positively impacts LA toward blended learning.
H4: PEU positively impacts PU of blended learning.
H5: PEU positively impacts IABL.

Learning Attitudes. Attitudes, as a psychological process, determine whether a person likes or dislikes something (Sreen et al., 2018; Balaman and Baş, 2021). Described as "the extent of a person's positive or negative judgment or evaluation of the action in issue" (Fishbein and Ajzen, 1975), a previous study highlighted the substantial empirical relationship between attitudes and willingness to continue (Ajzen, 1991). Subjective appraisal of participation in blended learning for students is reflected in their behavioral attitudes. Students' readiness to accept blended learning increases if they have positive attitudes toward participation in blended teaching. In contrast, if students' cognitive and emotional attitudes are insufficiently favorable to participate in blended learning, this situation can diminish students' desire to accept blended teaching (Tao et al., 2022). The better the college student's attitudes toward engaging in and using the blended learning model, the more that student is to accept it (Venkatesh et al., 2003; Wu and Liu, 2013). Therefore, this study proposes the following hypothesis:
H6: LA has a positive impact on IABL.

Subjective norms. The perceived social expectation regarding a certain behavior is denoted by SN (Bardus and Massoud, 2022; Collins et al., 2011; Chu and Chen, 2016). This notion applies to the concept that particular individuals or groups support and promote specific behaviors. (Han et al., 2020; Knauder and Koschmieder, 2019; Shalender and Sharma, 2021; Sungur-Gül and Ateş, 2021). In other words, if a large number of people who are significant to individuals do something that is beneficial for the environment, the individual in question also tend to be sufficiently sensitive or sensible to emulate this behavior (Ashaduzzaman et al., 2022; Cialdini et al., 1990; Hendy and Montargot, 2019). The SN associated with embracing blended learning refers to the expectations of and compliance demands made by classmates, professors, and other relevant groups when college students participate in blended learning. Therefore, university students are impacted by their peers, class norms, and professors' expectations. They are pushed by a variety of public viewpoints and may even feel alienated if they do not follow the standards thus expressed. SN significantly impacts the desire to utilize current instructional technologies in colleges and universities according to an empirical study by Venkatesh et al. (2003) and Asare et al. (2016). Nevertheless, previous research on whether SN influences students' readiness to adopt blended learning has not been thorough (Dakduk et al., 2018; Hadadgar et al., 2016; Prasad et al., 2018). Hence, the following hypotheses are proposed:
H7: SN positively impacts LA.
H8: SN positively impacts PBC.
H9: SN positively impacts IABL.

Perceived behavioral control. According to Ajzen (1991), PBC is one of the primary elements that impact the adoption of courses in blended learning. PBC relates to the degree to which students believe that they have control over their time, energy, and resources when participating in blended learning. In addition, PBC is beneficial for learners to improve their overall performance and academic accomplishment. In terms of PBC (or self-efficacy beliefs), MacFarlane and Woolfson (2013) reported specific relationships among a general sense of optimistic self-efficacy, reform implementation, and the ability to meet challenges. The intensity of PBC is primarily influenced by external facilitation circumstances and self-efficacy. First, external promotion factors mainly indicate the controllability of external conditions when students participate in blended learning, such as time and network equipment status. Oh and Yoon (2014) and Asare et al. (2016) claimed that a lack of external circumstances decreases students' desire to take online courses. Second, self-efficacy is related to the students' belief that they are qualified for blended learning. Students must examine the difficulty of a particular learning assignment, assess their ability's fit with the learning task in question, and assess their competence to complete the task. Therefore, this study proposes the following hypothesis:
H10: PBC positively impacts IABL.

The mediating roles of learning attitudes and perceived usefulness. Based on the preceding discussion and analysis of the relationships among PU, PEU, LA, and IABL, the higher the degree of PU of blended learning experienced by Chinese university students, the higher their LA toward participation, which positively influences IABL. Likewise, the higher the degree of PEU of blended learning experienced by Chinese university students, the higher their PU toward participation, which positively influences IABL. Moreover, active engagement in blended learning initiatives has the potential to stimulate university students' willingness to embrace this pedagogical method (Venkatesh et al., 2003; Wu and Liu, 2013).

LA is a mediating variable that positively influences Chinese university students' intention to adopt blended learning. Mustafa et al. (2021) found that PU can significantly influence users' intention to take advantage of a particular format of library resources through their positive attitudes. Jaiswal et al. (2021) concluded that changing the user's attitudes can increase the user's likelihood of exhibiting the intended adoption behavior and verified that people's attitudes toward EVs mediate the positive effect of PU on their adoption intention.

In summary, the following hypotheses are proposed:

H11: LA mediates the effect of PU on IABL.

H12: PU mediates the effect of PEU on IABL.

Based on these hypotheses, this study develops a conceptual framework by integrating the TAM and the TPB to explain university students' willingness to accept blended learning. Taking IABL as the explained variable, PU, PEU, IABL, SN, and PBC are regarded as explanatory variables (Fig. 1).

Research methodology

The study model underwent validation using structural equation modeling (SEM), which is a statistical method used to generate, estimate, and evaluate causal relationships. Unlike standard regression analysis, SEM can handle multiple dependent variables simultaneously as well as independent latent variables, thus facilitating the comprehensive examination and assessment of various theoretical models. Strong inferences from structural model testing, as shown in SEM treatments (Barrett, 2007; Kline, 2015), are contingent on a high sample size (i.e., at least 200 cases). Regarding the number of questionnaire samples, Loehlin (2004) discovered that the median of the paper data samples was 198 after counting 72 SEM papers. Barrett (2007) believed that the number of samples should be eight times greater than the number of model variables. However, he also noted that the built-in maximum likelihood method is generally utilized when SEM is implemented. The chi-square value becomes dramatically inflated as the sample size surpasses 500, resulting in poor model fit. As a result, scholars have generally recommended that the sample size be between 200 and 500. In addition, SEM represents a statistical technique that has been extensively employed to investigate the intricate interrelationships among multiple variables (Eksail and Afari, 2020). Within the scope of this study, meticulous scrutiny is directed toward the associations that exist between the observed variables and their underlying constructs, in line with the seminal work of Kline (2023). The present inquiry effectively harnesses the capabilities of SEM, as it allows for the simultaneous examination of variables while facilitating the independent estimation of the errors associated with each variable, as noted by Kline (2023). Moreover, this method facilitates the concurrent utilization of multiple indicator variables per construct, contributing to the generation of more robust inferences at the construct level when contrasted with conventional regression methodologies (Teo, 2009). Hence, SEM was deemed appropriate for this investigation. The research instrument and SEM are tested and reported separately in the next section.

Participants and procedure. University students drawn from various campuses across mainland China who were either enrolled at the time or had previously completed at least one blended learning course participated in the survey. They were invited to complete the surveys. In addition, the members of the project took the initiative to contact teachers responsible for blended teaching at various universities to learn more about the students' taking courses in blended learning. These teachers were asked to distribute paper or online surveys in the classroom. The university students completed the questionnaires voluntarily and were not compensated for their participation. From February through April 2022, a total of 233 questionnaires were collected. After excluding 32 incomplete and unclear surveys, 201 valid responses remained, resulting in an effective response rate of 86%. The outliers were removed because they might have led to inaccurate statistical results, according to Hair et al. (2012). The researchers utilized convenience sampling to select participants in this study, as this method offers certain advantages such as geographical proximity, easy accessibility, availability within a specific timeframe, and voluntary participation (Etikan et al., 2016). Based on the descriptive statistics of the sample, male students and female students accounted for 40.8% and 59.2% of the total population, respectively. Both undergraduate and postgraduate students at universities were included in the sample to provide a comprehensive representation of the student population. A total of 77.6% of the respondents were undergraduates, while 22.4% were postgraduates. The respondents' general information is as follows (Table 1).

Table 1 Demographics of respondents ($n = 201$).

Category	Number	Percent (%)
Gender		
Male	82	40.8
Female	119	59.2
Level of Study		
Undergraduate student	156	77.6
Postgraduate student	45	22.4
Study Discipline		
Social sciences	45	22.4
Arts and humanities	52	25.9
Engineering	37	18.4
Business and economics	54	26.9
Medical sciences	13	6.4

Research instrument. The researchers created the questionnaire based on previous comparable studies (Davis et al., 1989; Venkatesh et al., 2003; Wu and Liu., 2013; Ajzen and Fishbein, 2000) since no specialized questionnaire was available in the literature to directly collect feedback from Chinese university students. These inquiries were taken from these comparable studies and adjusted as necessary for this investigation. Because the outcomes of this discovering structure were not covered by the adopted instrument, only a few inquiries were added to the investigative tool. These initiatives were further modified to suit the current study context after being validated by previous studies on the technology acceptance of blended learning (see Table 2). Moreover, the items were back-translated by two scholars who were fluent in Chinese and English (Brislin, 1970). The instrument is divided into two sections: the first section records the demographic data of the respondents (see Table 1), while the second section contains questions intended to gauge the constructs included in the suggested theoretical model (see Table 2). Six latent variables are included in the scale design: PEU, PU, LA, SN, PBC, and IABL. Responses are scored on a seven-point Likert scale (ranging from 7: totally agree to 1: totally disagree) for the observed variables of each concept. The initial

Table 2 List of questions.

Construct	Construct Code	Variable measurement content	Variable source
Perceived ease of use	PEU1	The online and face-to-face class is easy and convenient to learn.	Davis et al., 1989
	PEU2	It is easier to participate in class discussions in blended learning.	Venkatesh et al., 2003
	PEU3	Becoming proficient in using blended learning is easy.	Wu and Liu., 2013
	PEU4	Blended learning follows a flexible schedule.	
Perceived usefulness	PU1	Blended learning has improved my efficiency.	Davis et al., 1989
	PU2	Blended learning can take into account the individual differences of students.	Venkatesh et al., 2003
	PU3	Blended learning has increased my awareness of active learning.	
	PU4	Blended learning helps to build a good teacher-student relationship.	
Learning attitudes	LA1	It is wise to use blended learning.	Davis et al., 1989
	LA2	Using blended learning is beneficial.	Venkatesh et al., 2003
	LA3	Blended learning courses are attractive.	
	LA4	Using blended learning can increase interest in learning.	
Subjective norms	SN1	My classmates think I should be actively involved in blended learning.	Ajzen and Fishbein, 2000 Venkatesh et al., 2003
	SN2	My teacher thinks I should be actively involved in blended learning.	
	SN3	My friends think I should be actively involved in blended learning.	
Perceived behavioral control	PBC1	I can effectively control the learning effect of blended learning.	Ajzen and Fishbein, 2000
	PBC2	I have enough time and energy to participate in blended learning.	Venkatesh et al., 2003
	PBC3	I am competent in a blended learning model.	
	PBC4	I can set goals based on learning materials.	
Intention to adopt blended learning	IABL1	I hope that there will be more blended learning in the curriculum in the future.	Venkatesh et al., 2003
	IABL2	I would actively recommend blended learning courses to others.	
	IABL3	Next semester I may also use blended learning.	

Table 3 Measurement model (convergent validity and reliability).

Construct	Item	Significance estimate				Topic reliability		CR	AVE	VIF
		Unstd. factor loading	S.E.	C.R.	P	Std. factor loading	SMC			
Perceived usefulness	PU1	1.000				0.846	0.715	0.877	0.642	1.970
	PU2	0.894	0.076	14.960	***	0.739	0.546			
	PU3	1.099	0.076	17.765	***	0.864	0.746			
	PU4	0.941	0.079	14.925	***	0.748	0.559			
Perceived ease of use	PEU1	1.000				0.800	0.640	0.822	0.537	1.659
	PEU2	0.977	0.092	10.638	***	0.780	0.546			
	PEU3	0.944	0.098	9.605	***	0.739	0.457			
	PEU4	0.935	0.093	10.100	***	0.706	0.499			
Learning attitudes	LA1	1.000				0.840	0.706	0.909	0.713	2.207
	LA2	1.021	0.067	15.222	***	0.868	0.753			
	LA3	0.921	0.067	13.783	***	0.814	0.662			
	LA4	0.987	0.066	14.873	***	0.855	0.730			
Subjective norms	SN1	1.000				0.851	0.724	0.822	0.608	2.016
	SN2	0.928	0.074	12.528	***	0.799	0.639			
	SN3	0.733	0.072	10.222	***	0.680	0.462			
Perceived behavioral control	PBC1	1.000				0.834	0.696	0.840	0.569	1.698
	PBC2	0.920	0.081	11.379	***	0.759	0.577			
	PBC3	0.996	0.085	11.725	***	0.779	0.607			
	PBC4	0.786	0.086	9.128	***	0.632	0.399			
Intention to adopt blended learning	IABL1	1.000				0.849	0.722	0.892	0.735	DV
	IABL2	1.040	0.070	14.800	***	0.854	0.729			
	IABL3	0.965	0.064	15.169	***	0.868	0.754			

SE Standard Error, *CR* Critical Ratio, *P* p-value, *SMC* Squared Multiple Correlations, *CR* Composition reliability, *AVE* Average variance extracted, *VIF* Variance information factor, *DV* Dependent variance.
***$p < 0.001$.

questionnaire consisted of four demographic questions and 24 items pertaining to the research model. First, a pilot test was conducted, and 46 test data points were collected for analysis. Two items that did not meet the relevant standards in terms of the modification indices were deleted based on the results of the analysis. Therefore, 22 items remained and were included in the formal questionnaire (see Table 2). The scales used were all derived from authoritative and mature questionnaires, which can to a certain extent guarantee the face and content validity of the questionnaires used. Simultaneously, this questionnaire was examined and debated by three professors working in the field of blended learning and received their unanimous affirmation, thus

Table 4 Analysis of discriminant validity (Fornell–Larcker Criterion).

Construct	Convergent validity	Discriminant validity					
	AVE	PU	PEU	LA	SN	PBC	IABL
PU	0.642	**0.801**					
PEU	0.537	0.582	**0.733**				
LA	0.713	0.688	0.674	**0.844**			
SN	0.608	0.668	0.648	0.697	**0.780**		
PBC	0.569	0.643	0.494	0.605	0.691	**0.754**	
IABL	0.735	0.713	0.675	0.732	0.727	0.653	**0.857**

Correlations among constructs are represented by off-diagonal values.
Values in bold are the square roots of AVE.

Table 5 Model fitting index.

Index	Model indicator values	Standard	Conclusion	Source
CMIN	366.740	The smaller, the better		
DF	198	The smaller, the better		
CMIN/DF	1.852	<3	Good fit	Hayduk, 1987
GFI	0.861	>0.8 Acceptable; >0.9 Good fit	Acceptable	Bagozzi and Yi, 1988
AGFI	0.822	>0.8 Acceptable; >0.9 Good fit	Acceptable	Bagozzi and Yi, 1988
CFI	0.940	>0.9	Good fit	Bagozzi and Yi, 1988
TLI (NNFI)	0.931	>0.9	Good fit	Hair et al., 2017
RMSEA	0.065	<0.08	Good fit	Hair et al., 2017
SRMR	0.077	<0.08	Good fit	Hu and Bentler, 1998

CMIN Chi-Square Minimum Fit Function, *DF* Degrees of Freedom, *CMIN/DF* Chi-Square to Degrees of Freedom ratio, *GFI* Goodness of Fit Index, *AGFI* Adjusted Goodness of Fit Index, *CFI* Comparative Fit Index, *TLI* Tucker-Lewis Index, *NNFI* Non-Normed Fit Index, *RMSEA* Root Mean Square Error of Approximation, *SRMR* Standardized Root Mean Square Residual.

further ensuring the face and content validity of the questionnaire.

Data analysis and results. SEM was used for data analysis due to its capacity to estimate numerous interconnected dependence connections based on observable and latent components while accounting for estimation errors (Hair et al., 2011). Fornell and Larcker (1981) provided three criteria to determine the convergent validity of the measurement model: (1) item reliability, (2) the composite reliability (CR) of each construct, and (3) the average variance extracted (AVE). Moreover, to assess item reliability, all item factor loadings were significant and greater than 0.50 (Hair et al., 2005). CR measures the internal consistency reliability of a latent construct. A threshold value of 0.70 or higher is often considered to be acceptable, indicating that the measures consistently represent the same latent construct (DeVellis, 2003). AVE quantifies the amount of variance hat is captured by a construct relative to measurement error. A threshold value of 0.50 or higher is typically considered to be adequate, suggesting that the construct explains more than 50% of the variance in its indicators (Fornell and Larcker, 1981). To evaluate discriminant validity, the square root of a specific construct's AVE was compared to its correlation with all other constructs. Discriminant validity was deemed acceptable if the square root of the AVE was larger than the correlations.

The constructs should be assessed before evaluating the model fit, thus verifying the reliability and validity of the questionnaire used in the study. The test is evaluated using four indicators: Cronbach's alpha, CR, AVE, and Variance Inflation Factor (VIF). In a confirmatory investigation guided by mature theories, Cronbach's alpha should be greater than 0.8, CR larger than 0.7, AVE more than 0.5, and VIF close to 3 or lower (Hair et al., 2009). In this study, the values of these indicators were calculated using SPSS 27.0 and AMOS 26.0 software (developed by IBM in Armonk), revealing that Cronbach's alpha was more than 0.8, CR was greater than 0.7, AVE was higher than 0.5, and VIF was lower than 3 (see Table 3). According to the results shown in Table 3, these claims held for all six constructs, suggesting that the proposed model satisfies the convergent validity criteria.

The validity test is used to assess discriminant validity between variables. A low correlation and a substantial difference between two latent variables are known as discriminant validity. Discriminant validity may be evaluated by comparing the square root of AVE to the correlation coefficient between variables. According to Fornell and Larcker (1981), a variable has high discriminant validity if the correlation coefficient between it and other variables is less than the square root of the AVE of the variable. The data shown in bold font in the table are the square root of the AVE, which is larger than all the values included in the table in which it is located, as shown in Table 4. Hence, the discriminant validity of the measurement model included in this study is acceptable and suitable.

Because SEM lacks a separate and powerful evaluation index such as traditional analysis techniques such as ANOVA and regression, it is frequently necessary to compare the covariance matrix of the sample to that of the theoretical model to evaluate its fit effect. AMOS software allows for 25 different types of fit indices, but not all of these indices must be reported. The most frequently reported indicators that measure the fitness of structural equation models are shown in Table 5. The aforementioned fit indices offer diverse viewpoints regarding the adequacy of the SEM, taking into account multiple dimensions of the model's intricacy and efficacy. Obtaining a comprehensive assessment of the model fit is often achieved by reporting multiple fit indices.

No fixed standard for fit indices has been universally established. While minimizing the chi-square value is desirable, the influence of sample size expansion on the chi-square value can affect its reference value. Hair et al. (2009) highlighted the potential significance of the chi-square statistic as sample size

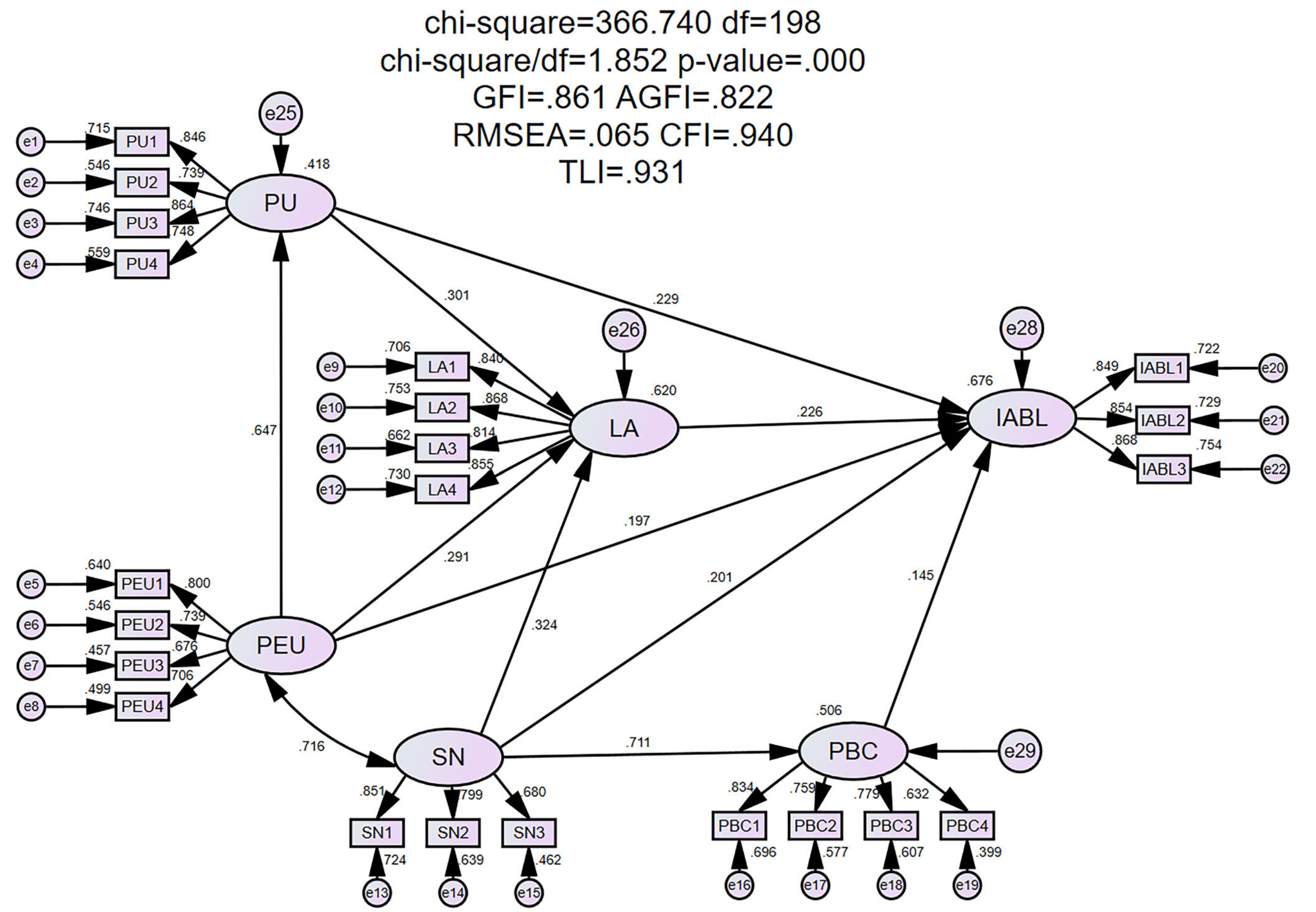

Fig. 2 Path diagram. Values on the straight arrows between variables represent the standardised path coefficients.

Table 6 Hypothesizes testing.

Hypothesis	Relationship	UnStd.	S.E.	C.R.	*P*	Std.(β)	Results	R^2
H1	PU → LA	0.308	0.083	3.728	***	0.301	Supported	0.620
H3	PEU → LA	0.322	0.128	2.518	0.012	0.291	Supported	
H7	SN → LA	0.313	0.091	3.436	***	0.324	Supported	
H4	PEU → PU	0.698	0.087	8.007	***	0.647	Supported	0.418
H8	SN → PBC	0.632	0.07	9.023	***	0.711	Supported	0.506
H2	PU → IABL	0.247	0.087	2.832	0.005	0.229	Supported	0.676
H5	PEU → IABL	0.229	0.132	1.739	0.082	0.197	Not Supported	
H9	SN → IABL	0.204	0.125	1.635	0.102	0.201	Not Supported	
H10	PBC → IABL	0.165	0.099	1.673	0.094	0.145	Not Supported	
H6	LA → IABL	0.237	0.099	2.394	0.017	0.226	Supported	

***$p < 0.001$.

increases. With respect to larger sample sizes, even minor deviations in the model can be magnified, leading to a statistically significant chi-square value. However, it is important to note that the significance of the chi-square statistic does not necessarily imply poor model fit. A significant chi-square value should not be automatically interpreted as indicating a lack of adequacy in the model (Hair et al., 2009).

Consequently, various indicators based on chi-square values have been developed, and the specific research context also influences the choice of fit index standards. For example, standards for fit indices differ between confirmatory and exploratory research, with exploratory research often employing lower standards than confirmatory research. Furthermore, variations in established standards exist. Therefore, researchers often consult the suggestions of authoritative scholars in the field of structural equations when evaluating model fit (Hayduk, 1987; Bagozzi and Yi, 1988; Hu and Bentler, 1998; Hair Jr et al., 2017). Table 5 presents the numerical findings and recommended values for the indices of the proposed model in this study. The goodness-of-fit indices meet the necessary threshold, indicating that the model is well-suited to the provided data based on comparative analysis.

Discussion

IBM AMOS 26 software was utilized in this research to effectively analyze the data and test the hypotheses within the framework of

SEM, thereby enhancing the rigor and accuracy of the study's findings. In this study, SEM analysis was employed for estimates, as was the validation of the conceptual framework by reference to statistical results and its links to outlier results (Shah and Goldstein, 2006). Figure 2 depicts the model after testing all six hypotheses collectively. The regression weights are indicated by the arrows. Table 6 summarizes the hypotheses.

According to Fig. 2 and Table 6, the following seven of the ten relationships indicated in the study framework were validated: PU → LA, PEU → LA, SN → LA, PEU → PU, SN → PBC, PU → IABL, and LA → IABL. PU ($\beta = 0.301$, $p < 0.001$), PEU ($\beta = 0.291$, $p < 0.05$), and SN ($\beta = 0.324$, $p < 0.001$) have a positive influence on LA toward blended learning, which explains 62% of the variation. This finding indicates that 62% of the variation in learners' attitudes variables could be explained by the three independent variables, i.e., PU, PEU, and SN. In addition, PEU ($\beta = 0.647$, $p < 0.001$) has a substantial impact on PU, collectively contributing 41.8% of the variance. Moreover, SN ($\beta = 0.711$, $p < 0.001$) significantly affects PBC, accounting for 50.6% of the variation. Among the factors affecting IABL, only two variables, i.e., PU ($\beta = 0.229$, $p < 0.01$) and LA ($\beta = 0.226$, $p < 0.05$), were significant, explaining 67.6% of the variance of the IABL variable; in contrast, the other three variables, i.e., PEU, SN, and PBC, were not significant.

In conclusion, the study found that PU, PEU, and SN had significant impacts on LA. SN had the greatest impact on LA, with a path coefficient of 0.324. This result indicated that higher levels of subjective norms were associated with higher levels of learning attitudes among Chinese university students. PU and PEU had the second and the third greatest impacts on LA, with path coefficients of 0.301 and 0.291, respectively, which also affected LA toward blended learning to a large extent. According to the data presented above, LA toward blended learning was more influenced by the people around the participants (or the environment in which they were located) in the post-epidemic situation. LA was also affected by this factor and became more positive. In addition, if it was more effective and convenient to engage in blended learning, this situation also improved LA toward blended learning as well as its acceptance. It can thus be concluded that the significance of PU, PEU, and SN with regard to determining LA was also proven in this investigation, echoing the findings of previous technology acceptance research (e.g., Davis et al., 1989; Venkatesh and Bala, 2008). When the present study's findings were compared to the data reported by previous studies, it was discovered that the effects of PU and PEU on LA are compatible with the propositions of Lee (2010). The relationship between SN and LA was also validated. This finding revealed that Chinese university students' perceptions of social expectations and pressures associated with BL were linked to their overall attitudes toward this learning approach. In other words, when Chinese university students perceive that their peers, instructors, or other influential individuals support or encourage blended learning, these perceptions might positively impact their attitudes and openness toward adopting this approach. This finding highlights the importance of SN in shaping Chinese university students' LA and acceptance of blended learning. This result suggests that creating a positive social environment that promotes and supports blended learning could have a favorable impact on Chinese university students' LA and willingness to engage with this learning method.

Moreover, the AMOS analysis indicated that PU and LA had a significant influence on IABL, accounting for 67.6% of the variance in IABL. In contrast, PEU, SN, and PBC had no significant impacts on IABL. The different effects of PU and PEU on IABL can be explained by reference to the two-factor theory proposed by Herzberg, an American behavioral scientist. Monitoring hygiene and motivation variables as per Herzberg's two-factor theory is a common approach used to determine the elements that drive satisfaction and motivation. In essence, this theory recognizes two sorts of factors: hygiene factors that contribute to student dissatisfaction and motivation factors that contribute to student satisfaction (Herzberg et al. 1959). Hygiene factors are critical in preventing dissatisfaction, while motivation factors are essential for promoting actual satisfaction (Herzberg, 1966). The former term refers to factors that are dispensable when they exist but cause user dissatisfaction if they do not exist, whereas the latter are factors that contribute to user satisfaction. According to the data collection and analysis, IABL is also driven by two elements, in which context PEU represents a hygiene factor and PU serves as a motivation factor. The PU of blended learning itself is widely considered by students to fall under the general needs of learners with regard to improving their learning, while PEU is a secondary factor. These findings are also compatible with those reported by Oh and Yoon (2014), indicating that university students may be more familiar with the operation of technology and have high learning capacity because they grew up in the Internet age. According to previous research, PEU, SN, and PBC have little effect on whether learners have IABL, but PU has a more significant impact in this context (Lee, 2010; Chen et al., 2012). The findings agree with those reported by Dakduk et al. (2018) and Prasad et al. (2018), demonstrating that persuasion and the public opinions of their peers, friends, instructors, or others have no impacts on Chinese university students' involvement in blended learning, which is rather a logical choice on their part. The reasons for this situation are as follows. One possible explanation is that learners prioritize the perceived benefits and advantages of blended learning as superior to other factors. PU is rooted in the TAM and suggests that individuals are more inclined to adopt a technology if they perceive it to be useful with regard to achieving their goals or fulfilling their needs. In the context of blended learning, learners may be motivated by potential benefits such as improved learning outcomes, enhanced access to resources, flexibility in learning, or increased engagement. Thus, when learners perceive blended learning as useful, they are more likely to develop an intention to adopt it. Additionally, this finding may be attributed to the evolving nature of technology and its integration into education. As blended learning continues to gain increasing recognition and prominence, learners might already possess a certain degree of familiarity and comfort with the use of digital tools and platforms. Therefore, the perceived ease of use of blended learning technologies may not be as influential in their decision-making process, as learners may have already overcome initial the usability challenges through their previous experiences with technology in education. Moreover, subjective norms and perceived behavior control might have limited influence due to the complex and individualistic nature of learners' decision-making processes. Because university students are mentally mature, they are conscious of the influence of blended learning on their cognitive thinking capacity and emotional attitudes. The IABL of Chinese university students may be more driven by personal motivations, learning preferences, and perceived self-efficacy than by external social pressures or perceived control over their behavior. Learners' perceptions of the usefulness of such learning may align more closely with their personal goals and motivations, making this factor a stronger predictor of their intention to adopt blended learning. The present blended learning strategy, on the other hand, is based on top-down promotion, which does not take into account students' subjective acceptance of the model and is more closely related to school affairs and the faculty. It is important to note that this finding is context-specific to the adoption of blended learning and may not necessarily apply to other educational contexts or technology adoption

Table 7 Mediation analysis.

Path	Effect type	Point Estimate	Product of Coefficients		Bootstrapping				Two-tailed significance
					Bias-Corrected 95% CI		Percentile 95% CI		
			S.E.	Z	Lower	Upper	Lower	Upper	
PU → LA → IABL	Total effect	0.710	0.070	10.143	0.563	0.843	0.567	0.846	***
	Direct effect	0.411	0.087	4.724	0.233	0.582	0.225	0.573	***
	Indirect effect	0.299	0.070	4.271	0.174	0.448	0.177	0.452	***
PEU → PU → IABL	Total effect	0.669	0.076	8.803	0.517	0.813	0.514	0.810	***
	Direct effect	0.403	0.075	5.373	0,258	0.551	0.252	0.546	***
	Indirect effect	0.267	0.057	4.684	0.167	0.394	0.162	0.387	***

scenarios. However, from an academic standpoint, this finding provides insights into the factors that influence learners' IABL and highlights the significance of emphasizing the PU of blended learning when promoting its adoption by Chinese university students.

Finally, to test for the existence of a mediating effect, we performed percentile bootstrapping and bias-corrected percentile bootstrapping (Taylor et al., 2008) on 5000 bootstrapped samples with 95% confidence intervals, examining PU, LA and PBC for three mediating variables. We followed the suggestion of Preacher and Hayes (2008) and calculated the confidence interval of the upper and lower bounds to test whether the indirect effect was significant. Significant summative effects were found in all paths studied. As shown in Table 7, the results of the bootstrap test confirmed the positive and significant mediating effect of LA in the relationship between PU and IABL (standardized indirect effect of 0.299, $p < 0.001$), and PU played a significant mediating role in the relationship between PEU and IABL (the standardized indirect effect was 0.267, $p < 0.001$). Therefore, H11 and H12 were supported. PU had a significant indirect positive effect on the IABL of Chinese university students through LA. PU improved the effect of attitudes on IABL. Simultaneously, PEU had a significant indirect positive effect on the IABL of college students through PU. For Chinese university students, more attention is given to the practical utility of blended learning, while less attention is given to the difficulty of participating in blended teaching. If students have strong perceptions of the actual effect of blended learning, these perceptions can promote their positive attitudes toward participating in blended teaching and thus enhance their willingness to accept blended teaching. Similarly, if students perceive the ease of participating in blended teaching more strongly, the effect of improving students' positive attitudes and willingness to participate in blended teaching is slightly weaker. To effectively implement the blended teaching model, it is essential to prioritize its usability while emphasizing student-centered approaches. By enhancing university students' learning experiences, the blended teaching model can demonstrate its remarkable practical value, thereby fostering increased acceptance of blended learning among a wider student population. Therefore, the tasks of optimizing student outcomes and creating an engaging learning environment should be a key focus, which can subsequently bolster students' willingness to embrace blended learning.

Implications

This research has important implications for future studies on how intention indicators may encourage learners to adopt blended learning.

Theoretical implications. As described in section 2, the theoretical grounds for this work were Davis's (1985) TAM and the TPB (Ajzen, 1985). The TAM was developed as a critical theory to justify and predict user acceptance of technology because it conceptualizes the elements that impact consumers' adoption of information system technology. Individuals' attitudes toward technology may explain their usage of technology according to the TPB. The current study contributes to this theoretical framework through an empirical analysis of the questionnaire findings to offer further evidence on blended learning. Similarly, by continuing research into blended learning in social studies classrooms at Chinese colleges, this study scientifically enhances scholarly understanding of this topic. This study is not only theoretically significant but also contributes to the corpus of scholarly and practitioner-based information concerning blended learning among university students.

The TAM and the TPB have been widely employed in technology acceptance research. However, these models have received criticism due to their perceived limitations, which have hindered their ability to effectively explain technology acceptance in academic contexts. This critique stems from their restrictive nature, which has led to an inadequate understanding of the complex dynamics underlying technology acceptance within educational environments. Notably, the close relationship between user-technology interaction and the educational setting highlights the need for a more comprehensive approach (Al-Emran et al., 2018). To address the limitations of the TAM and the TPB, researchers have increasingly embraced the integration of these two models. This integration aims to overcome the oversimplification inherent in these models and to develop a more comprehensive framework. The theoretical underpinnings of this research highlight ongoing discussions regarding the suitability of the TAM in educational contexts. The proposed model seeks to establish a cohesive framework by combining the TAM and the TPB to examine the factors influencing the adoption of blended learning in educational environments.

The findings of this study demonstrate that the research methodology employed in this context effectively supports the primary objective of the study. Specifically, the integrated model offers a robust theoretical foundation for explaining the adoption of blended learning. Furthermore, future studies are encouraged to explore the incorporation of additional theories alongside the TAM and the TPB. The Task-Technology Fit (TTF) Theory, the Unified Theory of Acceptance and Use of Technology (UTAUT), the Theory of Self-Regulation (TSR), and the Expectation Confirmation Model (ECM) are suggested as potential theories that can be referenced in future investigations. By incorporating these complementary theories, researchers can gain a more comprehensive understanding of the multifaceted factors that influence technology acceptance in educational contexts. This integrative approach can contribute to advancing knowledge in this field and provide valuable insights into practical applications.

Practical implications. To improve university students' attitudes toward blended learning and their perceived behavioral control, it is essential to focus on their actual needs. University students are autonomous and independent learners who prioritize their academic performance and cognitive development. Meeting university students' actual needs requires a combination of course content characteristics and learners' cognitive development. This approach not only allows knowledge to be transmitted and resources to be provided but also facilitates the cultivation of university students' innovative and autonomous learning abilities. Hence, it is crucial to promote the blended learning support system, including teaching content, methods, and platform design.

Blended learning places university students at the center and emphasizes the development of their autonomous learning abilities. The effectiveness of online teaching is largely dependent on the design of an online teaching platform with good functions, a user-friendly interface, and abundant resources. Teachers play an important role in this process by summarizing online learning content, providing guidance and motivation, and inspiring university students' thinking through interaction, discussion, and case analysis, thereby enhancing the interaction and synergy between online and offline learning. Furthermore, the effective implementation of blended learning requires the support of university management in terms of infrastructure, teaching staff, technical personnel, and student preparation. Management support is crucial for implementing blended teaching, and university management staff should play a vital role in providing instructional management and both psychological and emotional support for students. Additionally, it is important to enhance university students' self-efficacy and development of subjective consciousness. Blended learning combines various modes of learning, such as online, space-time, open, real-time, and community learning. To adjust to blended learning, university students require encouragement and guidance to boost their confidence and initiative with regard to participating in the course. Finally, student-oriented pedagogy should be advocated throughout the learning process, thereby encouraging university students to adopt proactive attitudes toward blended learning.

Limitations and directions for future research

Although this research performed substantial work to investigate the issue in question, the writers did not discuss this topic exhaustively. The study might thus have some drawbacks. First and foremost, because the study was performed in a metropolis, i.e., Guangzhou, the results are not generalizable. This type of quantitative research was performed through a small-scale, monocultural study based on a higher education context in China. University student samples are drawn from distinct contexts and groups. To evaluate the validity of these conclusions more effectively, future scholars are urged and encouraged to employ additional comparable study designs to investigate diverse samples of college students from varied academic backgrounds, such as different university backgrounds, various class sizes, and diverse professional programs. Additionally, because of the cross-sectional nature of the study (i.e., the data collected for the hypotheses were confirmed by distributing questionnaires at a particular moment in time), we could not completely comprehend the underlying dynamics from university students' perspectives. To overcome this limitation, future studies should employ a longitudinal approach to acquire a more thorough understanding of the dynamics associated with the variables over time. Furthermore, exploring other variables that may influence teacher acceptance of blended learning would be interesting. A qualitative study might be performed in pursuit of the same goal. As proposed by Arora and Saini (2013), probabilistic neural networks can be used to predict students' learning achievements in blended learning. The present study focused on students' opinions, but the perceptions of instructors and the administrative bodies of higher education institutions can also be considered to represent prospective research directions.

Conclusion

Against the backdrop of existing research, the main contributions and innovations of the study lie in its exploration of students' adoption of blended learning based on the TAM and the TPB from the perspective of Chinese undergraduates for the first time, thereby expanding the integrated theory of the TAM and the TPB. In addition, this paper contributes by providing a deeper knowledge of blended learning, particularly by identifying the path that improves its learning impact on university students in an innovative academic environment. Based on the TAM and TPB perspectives, data were acquired by administering a questionnaire that was completed by university students. According to a statistical study, the paths by which blended learning performance can be improved are that PU, PEU, and SN influence LA and PU affects PEU. Only PU and LA affect IABL. PEU, SN, and PBC, on the other hand, do not affect IABL. Based on these findings, four recommendations for enhancing higher education delivery through blended learning are provided. First, it is necessary to improve the curriculum's practicability and implement differentiated instruction. Moreover, in cases of limited resources, the faculty is advised to take advantage of the features of Chinese university students to teach them in a manner that depends on both their ability and their differences in various aspects of learning. Furthermore, teachers should focus on PU when designing courses to improve learning efficiency and the effectiveness of blended learning. As a result, a process of promoting blended learning awareness that extends from top administrators to learners should be implemented. Universities can create the majority of the materials and platforms needed to raise awareness of blended learning among teachers and students. Finally, it is essential to promote online functions and expand communication and engagement channels. Effective learning initiatives can influence learners' attitudes and behaviors; thus, teachers must remain up to date on current topics to ensure that they can adjust their teaching approaches to fulfill learners' needs in the future.

Data availability

The datasets analyzed during the current study are available in the Dataverse repository: https://doi.org/10.7910/DVN/PBJ2GY.

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Conceptualization: T.Y. Methodology: T.Y., C.W. Software: C.W. Writing—original draft preparation: T.Y., C.W. Writing—review and editing: T.Y., J.D., C.W. Supervision: J.D. Project administration: T.Y. Funding acquisition: T.Y. All authors read and approved the final manuscript. All authors have read and approved the re-submission of the manuscript.

Competing interests
The authors declare no competing interests.

Ethical approval
The author sought and gained ethical approval from the Research Ethical Board at Zhejiang University of Technology, and the study complied with ethical standards. There was no number attached to the approval.

Informed consent
The researcher sought and gained the consent of the participants to take part in the study. Out of the 233 sampled participants, all 233 accepted and voluntarily participated in the study after the researcher assured them of anonymity and that their responses were solely for academic purposes.

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