International Journal of Education and Practice
2024 Vol. 12, No. 3, pp. 797-818
ISSN(e): 2310-3868
ISSN(p): 2311-6897
DOI: 10.18488/61.v12i3.3758

Factors affecting in-service teachers' informatization instructional leadership in China

Wei Li[1]
Yoon Fah Lay[2+]

[1]*College of International Cooperation, Xi'an International University 710077, Shaanxi, China.*
[1]*Email: 450384173@qq.com*
[2]*Faculty of Psychology and Education, University Malaysia Sabah, Kota Kinabalu 88400, Sabah, Malaysia; Faculty of Social Sciences and Liberal Arts, UCSI University, Kuala Lumpur; School of Liberal Arts and Sciences, Taylor's University, Kuala Lumpur, Malaysia.*
[2]*Email: layyf@ums.edu.my*


(+ Corresponding author)

Article History
Received: 23 November 2023
Revised: 31 January 2024
Accepted: 16 February 2024
Published: 21 May 2024

Keywords
Behavioral intention
Blended teaching competence
Computer self-efficacy
PLS-SEM
Teachers' informatization instructional leadership
Use expectancy.

ABSTRACT

The ubiquity of instructional leadership integrated with technology has necessitated research into the application of instructional leadership and its influencing factors. The aim of this study is to investigate contributing factors to in-service teachers' informatization instructional leadership by determining the relationship between use expectancy, social influence, facilitating conditions, computer self-efficacy, blended teaching competence, behavioral intention and teachers' informatization instructional leadership. Quantitative research is employed using a questionnaire to collect data. The sample comprises 230 randomly selected in-service teachers from private undergraduate universities in Xi'an City, Shaanxi Province, China. Data analysis was carried out using SmartPLS. The results show that use expectancy, facilitating conditions, computer self-efficacy, blended teaching competence and behavioral intention all have a positive and significant effect on teachers' informatization instructional leadership. Use expectancy, computer self-efficacy and blended teaching competence have a positive and significant effect on behavioral intention, and behavioral intention significantly mediates the relationships between use expectancy, computer self-efficacy, blended teaching competence and teachers' informatization instructional leadership. The research provides practical guidance for universities attempting to implement or improve teachers' informatization instructional leadership practices. Efforts for policymakers to develop teachers' informatization instructional leadership should consider the importance of not only use expectancy and facilitating conditions but also computer self-efficacy, blended teaching competence, and the role of behavioral intention to use teachers' informatization instructional leadership.

Contribution/Originality: This study offers original insights into teachers' informatization instructional leadership in China. It extends theoretical knowledge by highlighting two intrinsic elements added into the UTAUT model. Furthermore, this study makes practical and theoretical recommendations for boosting teachers' informatization instructional leadership in universities.

1. INTRODUCTION

Due to the Covid-19 pandemic, the accelerated integration of technology into university classrooms has resulted in blended teaching. It was imperative for university teachers to understand the change and develop corresponding instructional leadership competence to transition to the complex teaching environment of both in-person and online teaching. This shift requires university teachers to adapt and incorporate technology into their instructional leadership process. Zh and Liu (2015) believe that teachers' informatization instructional leadership (TIIL) is a product of the combination of technology and teachers' instructional leadership in the context of the information age. TIIL is a comprehensive competence technology integrated into instructional management processes accompanied by blended teaching. In relation to this, Zhao (2019) believed that teachers' informatization instructional leadership includes three processes: building an informatization teaching environment, setting up rich online hybrid courses to guide students to independently self-study or conduct online interactive learning before and after face-to-face classes, and in-person informatization classroom instructional management. Why, therefore, should attention be given to the development of teachers' informatization instructional leadership and the variables that affect them? The main reason for developing informatization instructional leadership promotes the level of teachers' blended teaching and professional training in digital times. The attention to contributing factors benefits specific strategies and paths for improving teachers' informatization instructional leadership. If the level of TIIL is high, this will lead to positive interactive teaching and learning, a high level of blended teaching competence, innovative students with critical thinking skills, and a high level of informatization instructional management competence. Conversely, teachers who have no knowledge of informatization instructional leadership tend to be passive with regard to blended teaching. They display less creative thinking, lack innovative students, and often they only focus on fostering various skills in terms of teaching scope and ignore the development of teachers' informatization instructional leadership. The effective application of informatization instructional leadership among university teachers calls for knowledge of the contributing factors regarding technological infrastructure, resources, individual competence, and behavioral intention to adopt informatization instructional leadership.

Li (2020b) and Zh and Liu (2015) discussed the definition of TIIL from theoretical perspectives. Zhao (2019) examined the influence of resources and infrastructures and blended teaching competence on teachers' informatization instructional leadership using the first generation data analytical approach to assess the relationships between the endogenous variable and affecting factors. Venkatesh, Morris, Davis, and Davis (2003) proposed the Unified Theory of Acceptance and Use of Technology (UTAUT) to explain the intention to adopt and use a technology. UTAUT contains four core independent variables: performance expectancy (PE), effort expectancy (EE), social influence (SI) and facilitating conditions (FC); a mediating variable: behavioral intention (BI); and four moderating variables: gender, age, experience, and voluntary use. UTAUT synthesizes eight main theoretical models: Theory of Reasoned Action (TRA), the Technology Acceptance Model (TAM), the Theory of Planned Behavior (TPB), the Motivational Model (MM), the Innovation Diffusion Theory (IDT), the Model of Personal Computer Utilization (MPCU), and Social Cognitive Theory (SCT). Although the UTAUT model has been successfully applied to a large number of situations in predicting behavior and intention, it has not been fully leveraged in the field of instructional management in digital times. This study is based on the UTAUT model and supposes that use expectancy (UE), PE, EE, SI, FC, computer self-efficacy (CSE), blended teaching competence (BTC), and behavioral intention (BI) directly affect TIIL. It is assumed that UE, SI, FC, CSE, and BTC also directly influence BI to adopt TIIL. Additionally, it is also assumed that UE, SI, FC, CSE, and BTC indirectly influence TIIL through BI. To this end, the objective of this study is to test the hypotheses by assessing the significant relationships among the constructs in the proposed structural model to explore contributing factors to TIIL using the partial least squares structural equation modeling (PLS-SEM) approach as an advanced second-generation analytical technique.

2. LITERATURE REVIEW

2.1. Use Expectancy (UE)

In this study, use expectancy (UE) includes two dimensions: performance expectancy (PE) and effort expectancy (EE). PE is defined as the extent to which an individual considers that utilizing a system will help to enhance job performance (Venkatesh et al., 2003). Bandura (1986) asserted that human action is based upon a type of action-outcome expectancy. Bandura (1986) advocated that action-outcome expectancy is assumed to impact behavior via its influence on goals or intentions to engage in the behavior. Performance expectancy significantly predicts behavioral intention (Ain, Kaur, & Waheed, 2016; Mikalef, Pappas, & Giannakos, 2016). Many studies based on the UTAUT model have shown that performance expectancy influences the behavioral intention to use a technology (Nandwani & Khan, 2016; Prasad, Maag, Redestowicz, & Hoe, 2018).

Venkatesh, Thong, and Xu (2012) defined effort expectancy as the degree of ease related to the system use and individuals' perception of the ease or difficulty of operating devices/tools. Effort expectancy is used to assess if the adoption of teachers' informatization leadership is easy to understand and master. Ifedayo, Ziden, and Ismail (2021) believe that effort expectancy determines the intention to exhibit a certain behavior. Innovation Diffusion Theory (IDT) notes that relative advantage, complexity, compatibility, trialability and observability predict behavior use, i.e., effort expectancy for complexity predicts teachers' adoption of informatization leadership. Empirically, Ifedayo et al. (2021) discovered that effort expectancy positively predicted individual behavioral intention to adopt technology tools/devices/platforms. Valtonen et al. (2015) indicated that the effect of effort expectancy had a significant effect on behavioral intention. In contrast, effort expectancy had an insignificant impact on behavioral intention in several emerging studies (Lin, Huang, & Ko, 2020; Raman & Don, 2013).

The mediating effect is the process of examining a factor's interfering function (Kang, Liew, Lim, Jang, & Lee, 2015). Theoretically, behavioral intention mediates the relationship between UE and behavior. According to the UTAUT used by Venkatesh et al. (2003) the effect of UE, including PE and EE, on behavior is mediated through behavioral intention. Additionally, many studies have justified the mediating effect of behavioral intention between use expectancy and use behavior (Ameri, Khajouei, Ameri, & Jahani, 2020; Baydas & Goktas, 2017; Ifedayo et al., 2021).

2.2. Social Influence (SI)

Venkatesh and Davis (2000) explained social influence as employees who utilize a system with the intent to potentially influence other peers to adopt that system. Bandura's social cognitive theory (SCT) also recognizes that an individual's behaviors occur in a specific social context. These behaviors are influenced by observation from an individual's peers. In addition, Baydas and Goktas (2017) asserted that learning a behavior depends on how others perform the behavior and the results they achieve from it. Attuquayefio and Addo (2014) stated that the more similar the model and spectators are in personality, age and status, the higher the possibility that people will follow a behavior. To this end, social influence can impact the formation of one's behaviors.

The relationship between SI and BI is discussed from various perspectives. Some research shows that SI directly affects BI (Teo, Huang, & Hoi, 2018) and insignificantly impacts BI in the education context. Furthermore, some research indicates that SI has no impact on BI (Raman & Thannimalai, 2021; Thongsri, Shen, Bao, & Alharbi, 2018). In addition, Raman and Don (2013) and Tarhini, Masa'deh, Al-Busaidi, Mohammed, and Maqableh (2017) found that SI significantly affected BI and played a crucial part in augmenting behavioral intention. The UTAUT model also supports the idea that SI predicts BI.

The UTAUT in Venkatesh et al. (2003) asserts that the effect of SI on behavior is mediated through behavioral intention. In fact, many studies justify the mediating effect of behavioral intention on social influence and use behavior (Ameri et al., 2020; Baydas & Goktas, 2017; Radovan & Kristl, 2017; Testa & Tawfik, 2017). Ifedayo et al. (2021) also discovered that behavioral intention significantly mediated the variance changes in the relationship between SI and use behavior.

2.3. Facilitating Conditions (FC)

Park, Lee, and Yi (2011) describe facilitating conditions as how an individual thinks that an organization provides technical infrastructure to support the use of technology or systems. Facilitating conditions (FC), grounded in the Theory of Planned Behavior (TPB), represents perceived behavioral control and is a variable that predicts information system use behavior, which is in alignment with the UTAUT model in which FC directly determines technology user behavior. Empirically, FC has been found to significantly affect technology use behavior (Perera & Abeysekera, 2019; Prasad et al., 2018; Raman & Thannimalai, 2021; Venkatesh et al., 2012).

The UTAUT model asserts that FC doesn't influence the intention to adopt information technology, but it directly affects behavior. However, studies argue that if an environment of support exists or there is a policy for motivating and pushing technology utilization, individuals have the intention to use technology and exhibit use behavior. Ain et al. (2016) found that poor FC negatively influences technology use among English teachers in China due to insufficient technical assistance and technical training. In contrast, better FC encouraged teachers to use computers (Salloum & Shaalan, 2019; Zh & Liu, 2015). Many studies have also found that FC directly predicts BI (Alyoussef, 2021; Baydas & Goktas, 2017; Tseng, Lin, Wang, & Liu, 2022).

The assertion that behavioral intention mediates the relationship between FC and behavior is determined by the TPB Ajzen (1991) in which FC is among the resources and perceived facilitation. Since perceived behavioral control (PBC) depends on control beliefs and perceived facilitation affects behavior via intention, FC as a sub-element of PBC affects behavior via intention. Intention has been emphasized to have a significant mediating effect on PBC and behavior. Similarly, behavioral intention mediates the relationship between FC and behavior. Furthermore, Alyoussef (2021) and Tseng et al. (2022) justified that FC indirectly predicts use behavior, with behavioral intention as a mediator. This finding has broken through the original construct relationship in the UTAUT model in which behavioral intention has no mediating effect on the relationship between FC and use behavior; behavioral intention only directly predicts use behavior.

2.4. Computer Self-Efficacy (CSE)

Compeau and Higgins (1995) described computer self-efficacy as the evaluation of an individual's ability to use a computer; this evaluation was made regarding the capability to use computer technology for a wider range of projects. Marakas, Johnson, and Clay (2007) asserted that computer self-efficacy is modified from the self-efficacy construct to the computer use context. Karsten, Mitra, and Schmidt (2012) stated that computer self-efficacy significantly influenced individual cognition, emotions and behaviors, and it correlated significantly with the behavioral intention to use computers.

Regarding the relationship between computer self-efficacy and behavioral intention, some research in China discovered that CSE is a significant antecedent for teachers' behavioral intention to use technology (Radovan & Kristl, 2017; Teo et al., 2018).

According to the Theory of Planned Behavior, CSE measures the likelihood of a person having the skills (efficacy) necessary to perform a behavior. Since perceived behavioral control depends on control beliefs, and perceived facilitation affects behavior via the influence of intention, it is scientific to infer that the impact of computer self-efficacy as a kind of efficacy related to teachers' informatization instructional leadership behavior is mediated through intention.

2.5. Blended Teaching Competence (BTC)

Based on Feng, Wang, and Wu (2018) the concept of blended learning can be analyzed in two dimensions—physical and pedagogical characteristics—and can be divided into the technology application stage, the technology integration stage and the "Internet+" stage. Blended learning has undergone a developmental shift from online learning content to online instructional design, with emphasis on the learning experience. The focuses of the different phases are on technology, teachers, and students, respectively. Ellis, Goodyear, O'Hara, and Prosser (2007) pointed out that blended teaching competence requires teachers not just to mix face-to-face and online instruction but mix teaching and tutoring in a "student-centered" learning environment. Additionally, it requires teachers to have skills in technology-mediated interaction, digital content, face-to-face interaction and non-digital content respectively based on the three teaching modalities (traditional teaching, online teaching, and blended teaching).

The Theory of Planned Behavior proposed by Ajzen (1991) underscores the relationships among perceived behavioral control, intention, and behavior. Perceived behavioral control focuses on the likelihood and importance of the skills necessary to successfully perform a behavior. Ajzen (1991) asserts in theory of planned behavior that there are three construct relationships—that perceived behavioral control directly affects behavior, perceived behavioral control directly influences intention, and perceived behavioral control indirectly predicts behavior through mediating intention. Logically, it can be inferred from the theory of planned behavior that blended teaching competence as a skill, which is a form of control belief and perceived facilitation believed necessary, can be used to measure teachers' informatization instructional leadership behavior, that BTC can be used to predict behavioral intention, and that BTC can directly affect teachers' informatization instructional leadership behavior through behavioral intention.

Empirically, Zhao (2019) found that there was a significant and positive correlation between blended teaching competence and teachers' informatization instructional leadership. Some studies related to blended teaching competence were mainly in the scope of teaching (Pulham & Graham, 2018; Yang, Zhang, Chai, & Xu, 2022) but the study approach using PLS-SEM to analyze the interrelation between blended teaching competence and behavior has not been extensive in the perspective of teaching management. Hence, we expect that blended teaching competence is positively related to behavioral intention to use technology in instructional leadership, as well as associated with teachers' use of informatization instructional leadership in this study.

2.6. Behavioral Intention (BI)

Based on Theory of Planned Behavior, behavioral intention can be understood as: how hard teachers are willing to perform a behavior; how much of an effort they are planning to exert in order to perform a behavior. This study investigates if university teachers have behavioral intention to apply informatization instructional leadership. According to the technology acceptance model (TAM) by Davis (1989) and the TAM2 by Venkatesh and Davis (2000) behavioral intention predicts the actual system use or use behavior. System use is determined by behavioral intention. In addition, the UTAUT model has identified that behavioral intention is both an exogenous variable and an endogenous variable, which is a predictor of an individual's use behavior. Hence, in this study it can be inferred that behavioral intention among in-service teachers is the inner motive to adopt technology in instructional leadership process.

Research on the relationship between behavioral intention to use technology and teachers' instructional leadership is still scarce. Hence, this research attempts to investigate the relationships between behavioral intention (BI) and teachers' informatization instructional leadership (TIIL) and explore the mediating effect of BI between the exogenous variables and TIIL.

2.7. Teachers' Informatization Instructional Leadership (TIIL)

Zh and Zhang (2016) advocated that teachers' informatization instructional leadership consolidates conceptions of informatization teaching, informatization leadership, and teachers' instructional leadership, which is the product of teachers' teaching, teachers' leadership and teachers' instructional leadership integrated with information technology/devices in the digital age. Literature involving the various research perspectives of teachers' informatization instructional leadership has been increasing year by year (Chua & Chua, 2017; Jaipal-Jamani et al., 2018; Kaboodvand, 2020; Li, 2020b; Raman & Thannimalai, 2019; Thannimalai & Raman, 2018; Zh & Liu, 2015; Zh & Zhang, 2020; Zhu & Zhang, 2019).

Empirically, Zhao (2019) explored factors affecting teachers' instructional leadership using the AMOS-SEM approach. From the perspective of teachers' informatization instructional leadership process, TIIL includes three dimensions: Informatization Teaching Environment Construction (ITEC), Informatization Extracurricular Learning Leading (IELL), and Informatization Classroom Teaching Management (ICTM), Beyond that, Zh and Zhang (2020) found that teachers' information technology leadership had a strong effect on teaching efficacy. Thus, we attempt to explore the contributing factors to teachers' informatization instructional leadership as the endogenous variable in this research.

2.8. Theoretical Framework

Based on the description above, a theoretical framework on the factors that affect the application of teachers' informatization instructional leadership was proposed.

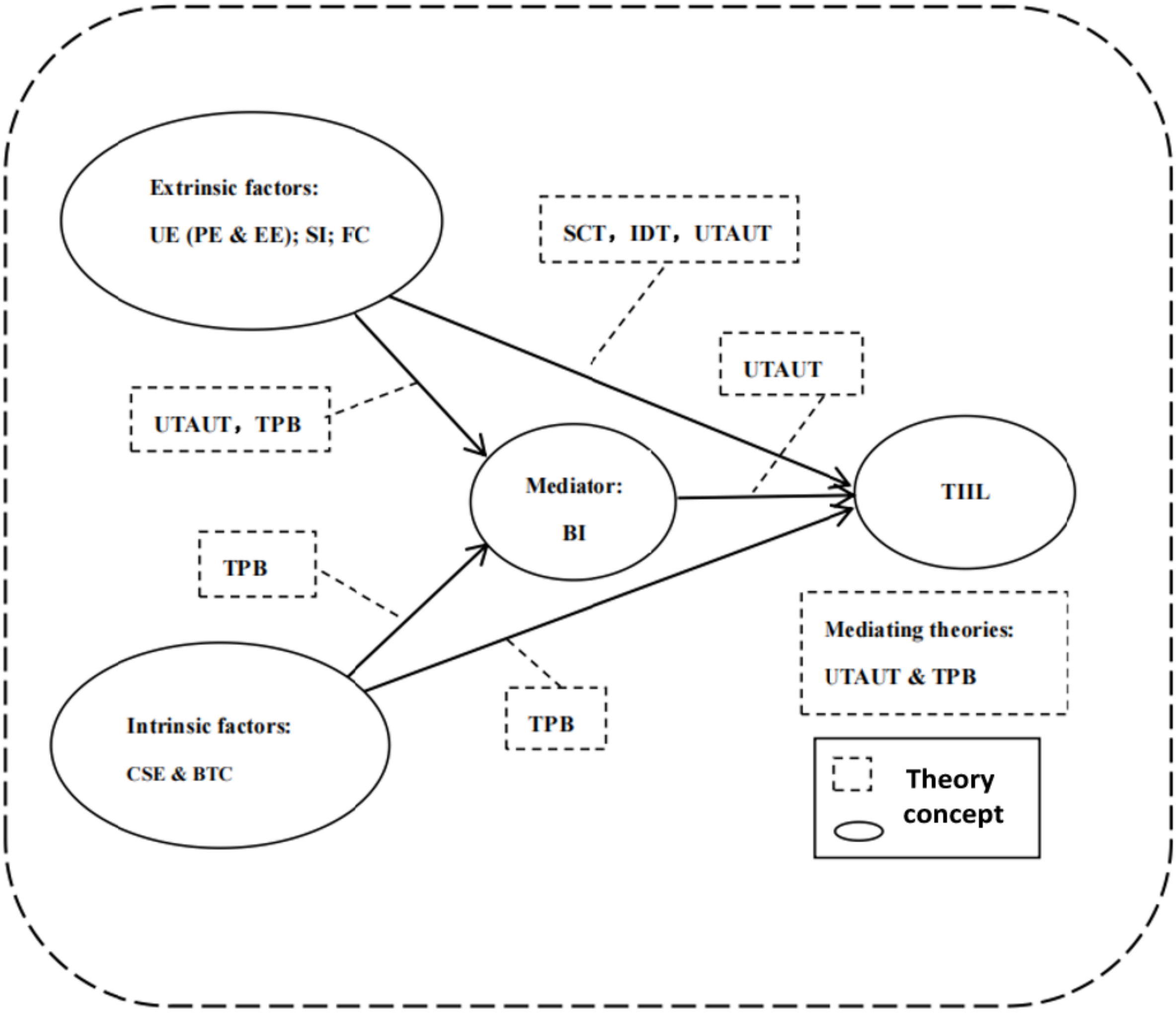

Figure 1. Theoretical framework of factors affecting the application of teachers' informatization instructional leadership.

Note: SCT: Social cognitive theory.
IDT: Innovation diffusion theory.
TPB: Theory of planned behavior.
UTAUT: Unified theory of acceptance and use of technology.
UE: Use expectancy, SI: Social influence, FC: Facilitating conditions, CSE: Computer self-efficacy, BTC: Blended teaching competence, BI: Behavioral intention, TIIL: Teachers' informatization instructional leadership.

Figure 1 illustrates the theoretical framework of this study in which items in circles represent concepts and items in rectangles represent theory. Teachers' informatization instructional leadership (TIIL) is the exogenous variable of this study. TIIL is affected by independent variables through the moderating variable of BI. Independent variables contain intrinsic factors (use expectancy including performance expectancy and effort expectancy, social influence and facilitating conditions) and extrinsic factors (computer self-efficacy and blended teaching competence). The direct predictive relationships between the extrinsic factors and TIIL are explained by theories (UTAUT, SCT and IDT). The direct predictive relationships between the intrinsic factors and TIIL are explained by the theory of planned behavior. The predictive relationship between the moderating variable (BI) and TIIL is explained by the UTAUT.

In addition, the direct predictive relationships between the extrinsic factors and BI are explained by UTAUT and the TPB, whereas the direct predictive relationships between the intrinsic factors and BI are explained by the TPB. Beyond that, the relationship between the intrinsic factors and TIIL through a moderating variable (BI) are explained by the UTAUT and TPB. Similarly, the relationship between the extrinsic factors and TIIL through a moderating variable (BI) are explained by the UTAUT and the TPB.

2.9. Hypotheses

H_1: UE has positive and significant effect on TIIL.

H_2: SI has positive and significant effect on TIIL.

H_3: FC has positive and significant effect on TIIL.

H_4: CSE has positive and significant effect on TIIL.

H_5: BTC has positive and significant effect on TIIL.

H_6: BI has positive and significant effect on TIIL.

H_7: UE has positive and significant effect towards BI.

H_8: SI has positive and significant effect towards BI.

H_9: FC has positive and significant effect towards BI.

H_{10}: CSE has positive and significant effect towards BI.

H_{11}: BTC has positive and significant effect towards BI.

H_{12}: BI mediates the relationship between UE and TIIL.

H_{13}: BI mediates the relationship between SI and TIIL.

H_{14}: BI mediates the relationship between FC and TIIL.

H_{15}: BI mediates the relationship between CSE and TIIL.

H_{16}: BI mediates the relationship between BTC and TIIL.

3. RESEARCH METHODOLOGY

3.1. Population and Sample

Figure 2 the population for the study, which comprises in-service teachers from nine private (not government-funded) undergraduate universities located in Xi'an City, Shaanxi Province, China. The nine private universities are classified into four clusters according to their comprehensive ranking based on the Chinese Ministry of Education (2022). The sampling includes the purposive sampling technique for the first stage and the random cluster sampling technique for the second stage. The first stage excludes four private undergraduate universities that don't completely conduct blended teaching, which is an essential criterion for adopting teachers' informatization leadership to meet the sampling requirements for this study. Random sampling was conducted to randomly select another four universities (XAIU, XFYU, XSYU, XTEI) respectively representing four clusters in the second stage. A total of 230 in-service teachers were finally randomly selected as the research sample from a total of 1,645 teachers from four different clusters of universities. Among them, 58 in-service teachers are from University A with a total population of 456; 58 in-service teachers are from University B with a total population of 387; 58 in-service teachers are from University C with a total population of 365; and 56 in-service teachers are from University D with a total population of 437.

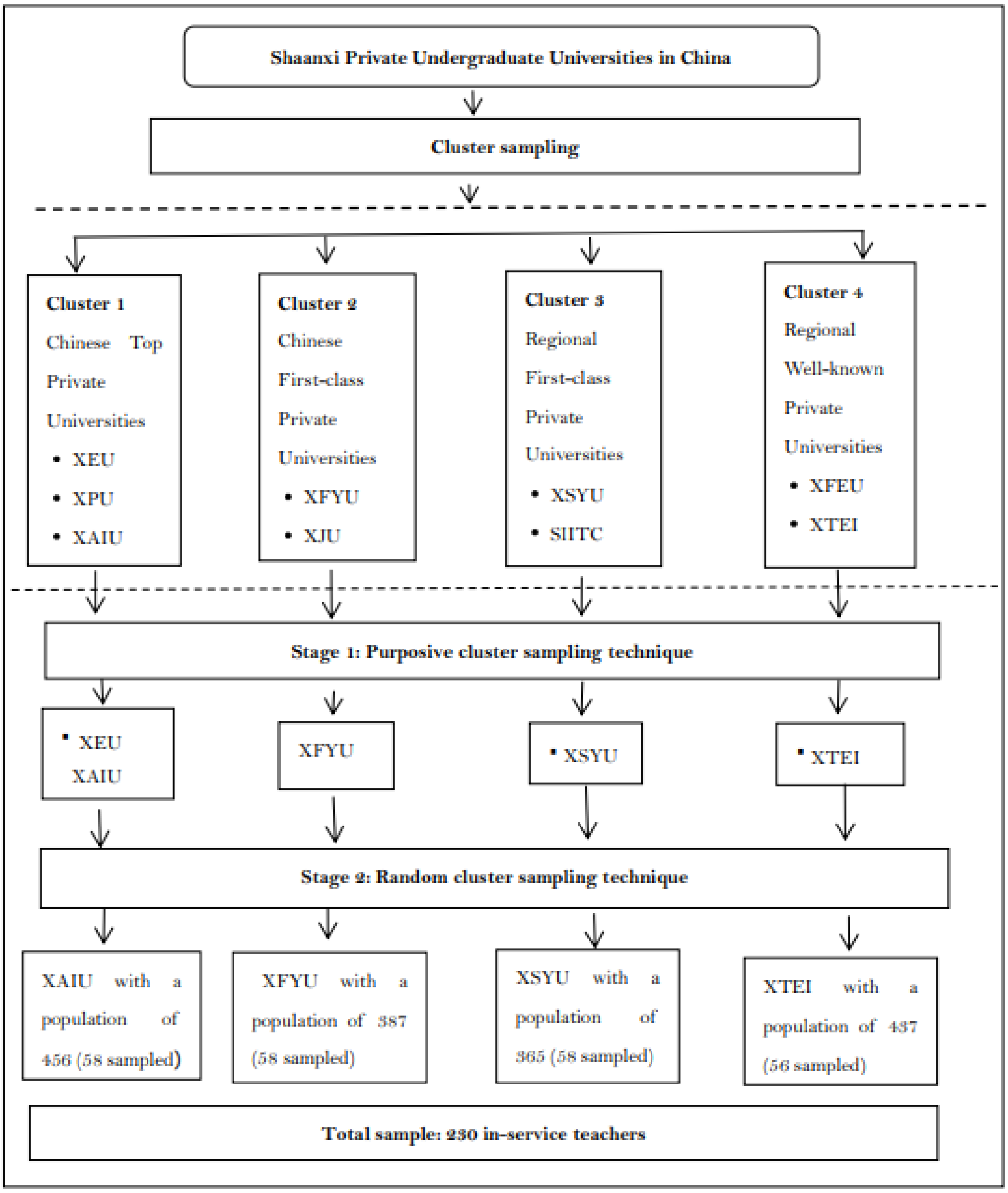

Figure 2. Population and sampling technique.

Source: Chinese Ministry of Education (2022).

3.2. Instruments

The survey questionnaire consisted of seven scales with a total of 77 items: Use Expectancy Scale (10 items), Social Influence Scale (5 items), Facilitating Conditions Scale (5 items), Computer Self-Efficacy Scale (5 items), Blended Teaching Competence Scale (32 items), Behavioral Intention Scale (5 items), and Teachers' Informatization Instructional Leadership Scale (15 items). To use the PLS-SEM approach to analyze the data, all scales were adapted and changed into 11-point semantic differential scales ranging from 0 representing Strongly Disagree to 10 representing Strongly Agree.

Prior to the actual study, a pilot study was conducted with 60 in-service teachers from four universities of XAIU, XFYU, XSYU, and XTEI to examine the instrument's reliability and validity. After the assessment using SmartPLS, there were a total of nine items eliminated from the original 77 items in the questionnaire due to factor loadings below 0.40; the outer loadings of 68 items were all higher than 0.708. The composite reliability and Cronbach's alpha values of the remaining 68 items are all higher than 0.70 (see Table 1). The average variance extracted (AVE) values of the 68 items are all greater than 0.50. The cross-loading and Fornell–Larcker criteria have all met the requirements. The heterotrait-monotrait ratio (HTMT) of the 68 items is less than 0.90. All of these results indicate that the reliability and validity of the instrument have been established.

Table 1. Criteria for assessing the reliability and validity for the PLS-SEM.

Assessment	Criteria
Reliability and validity Internal consistency reliability	Composite reliability • 0.60–0.70 accepted (Hair, Hult, Ringle, & Sarstedt, 2017). • < 0.60 rejected (Hair et al., 2017).
Indicator reliability	Outer loading • > 0.70 accepted (Hair et al., 2017). • < 0.40 rejected (Hair et al., 2017).
Convergent validity	Average variance extracted (AVE). • > 0.50 (Hair et al., 2017).
Discriminant validity	Cross-loading • The indicator's outer loading on the associated construct should be greater than any of its cross-loadings on other constructs (Hair et al., 2017). Fornell–Larcker criterion • The square root of each construct's AVE should be greater than its highest correlation with any other construct (Henseler, Ringle, & Sarstedt, 2015). Heterotrait-monotrait ratio (HTMT) • HTMT < 0.90 accepted (Hair et al., 2017). • HTMT > 0.90 lack of discriminant validity (Hair et al., 2017).

3.3. Procedure and Data Collection

Prior to collecting the data, the application to conduct the research was approved by the teachers' development center from each of the four universities. The data collection process was carried out in November and December 2022 during COVID-19. The questionnaire was created in Chinese Questionnaire Star Form. It was written in English and Chinese, and validity was ensured through a translation process involving an expert and a third party. After explaining the purpose of the study to each participant, informed consent was obtained. The questionnaire was explained and distributed via the WeChat platform to elect in-service teachers from four universities (A, B, C, and D) with the help of peer teachers during routine weekly meeting. The respondents voluntarily and anonymously responded to the questionnaire. A final total of 230 responses were received from 1,645 in-service teachers from four private undergraduate universities via the WeChat online platform.

3.4. Data Analysis

After collecting the 230 questionnaires, SPSS 25.0 software was used to identify missing data, suspicious response patterns, outliers, and data distribution. Based on the analysis results, two suspicious response patterns and one outlier were removed from the data set. All missing patterns were considered to be missing at random. The missing values were then imputed using an expectation–maximization (EM) algorithm. The final sample consisted of 227 questionnaires.

4. FINDINGS

4.1. Reliability and Validity

Hair et al. (2017) suggests that SmartPLS software is a powerful tool for assessing the reliability and validity of research instruments based on three criteria: Composite reliability (CR) and Cronbach's alpha (CA) coefficient determining the internal consistency reliability for instruments; the average variance extracted (AVE) and outer loading examining convergent validity; and the Fornell–Larcker criterion, cross-loadings, and the heterotrait-monotrait ratio (HTMT) assessing the discriminant validity of all items. Additionally, the constructs' reliability is established if the composite reliability (CR) and Cronbach's alpha (CA) exceed 0.70. An AVE that is more than 0.50 represents convergent validity. Outer loadings higher than 0.40 meet the criterion. The Fornell–Larcker criterion states that the AVE's square root of all constructs should exceed their highest correlation with any other construct. For the cross-loadings, any indicator's outer loading value of the corresponding structure must exceed their cross-loading values from other structures. A HTMT less than 0.90 indicates that discriminant validity has been established.

Table 2. Reliability and validity results.

Reflective second-order constructs	Item	Outer loading	Cronbach's alpha	Composite reliability (CR)	AVE
BI	BI_1	0.919	0.93	0.95	0.827
	BI_2	0.931			
	BI_3	0.910			
	BI_5	0.878			
BTC	BTC_ER	0.708	0.911	0.928	0.617
	BTC_FSSI	0.759			
	BTC_FTSI	0.784			
	BTC_MBLE	0.700			
	BTC_PBA	0.792			
	BTC_PBAS	0.832			
	BTC_PI	0.833			
	BTC_TL	0.860			
CSE	CSE_1	0.860	0.882	0.918	0.737
	CSE_3	0.883			
	CSE_4	0.866			
	CSE_5	0.825			
FC	FC_1	0.794	0.866	0.909	0.715
	FC_2	0.883			
	FC_3	0.876			
	FC_5	0.826			
SI	SI_1	0.819	0.877	0.914	0.727
	SI_2	0.822			
	SI_3	0.906			
	SI_4	0.860			
TIIL	TIIL_ICTM	0.884	0.87	0.92	0.794
	TIIL_IELL	0.901			
	TIIL_ITEC	0.888			
UE	UE_EE	0.889	0.742	0.886	0.795
	UE_PE	0.894			

Note: BI = Behavioral intention; BTC = Blended teaching competence; ER = Evaluating and reflecting; FSSI = Facilitating student-student interaction; FTSI = Facilitating teacher–student interaction; MBLE = Managing blended learning environment; PBA = Planning blended activities; PBAS = Planning blended assessment; PI = Personalizing instruction; TL = Technical literary; CSE = Computer self-efficacy; FC = Facilitating conditions; SI = Social influence; TIIL = Teachers' informatization instructional leadership; ICTM = Informatization classroom teaching management; ITEC = Informatization teaching environment construct; IELL = Informatization extracurricular learning leading; UE = Use expectancy.

Table 2 shows that all research constructs with UE, SI, FC, CSE, and BTC as second-order constructs are reliable and valid, as they all have composite reliability (CR) and Cronbach's alpha (CA) values greater than 0.60, AVE values more than 0.50, and outer loading values higher than 0.40; therefore, none of the items need to be eliminated.

Table 3 shows the cross-loading for each item with respective constructs for UE, SI, FC, CSE, and BTC as second-order constructs. All bolded outer-loading values for the items which measured each particular construct have shown greater values than any of their cross-loading constructs, which meets the criteria of discriminant validity in terms of cross-loadings.

Table 3. Cross-loading results.

Cross-loading	BI	BTC	CSE	FC	SI	TIIL	UE
BI_1	**0.919**	0.442	0.468	0.387	0.295	0.541	0.444
BI_2	**0.931**	0.496	0.418	0.375	0.340	0.555	0.460
BI_3	**0.910**	0.435	0.415	0.367	0.304	0.513	0.420
BI_5	**0.878**	0.488	0.465	0.360	0.290	0.533	0.453
BTC_ER	0.386	**0.708**	0.350	0.275	0.337	0.367	0.310
BTC_FSSI	0.383	**0.759**	0.330	0.271	0.271	0.400	0.384
BTC_FTSI	0.368	**0.784**	0.342	0.310	0.360	0.408	0.351
BTC_MBLE	0.285	**0.700**	0.315	0.313	0.301	0.428	0.369
BTC_PBA	0.404	**0.792**	0.485	0.507	0.477	0.561	0.512
BTC_PBAS	0.450	**0.832**	0.550	0.511	0.549	0.527	0.488
BTC_PI	0.429	**0.833**	0.446	0.392	0.441	0.485	0.449
BTC_TL	0.484	**0.860**	0.477	0.512	0.471	0.555	0.509
CSE_1	0.414	0.439	**0.860**	0.717	0.375	0.555	0.466
CSE_3	0.409	0.440	**0.883**	0.626	0.383	0.565	0.403
CSE_4	0.499	0.554	**0.866**	0.582	0.430	0.576	0.496
CSE_5	0.322	0.379	**0.825**	0.572	0.320	0.445	0.343
FC_1	0.315	0.399	0.545	**0.794**	0.540	0.429	0.400
FC_2	0.409	0.429	0.661	**0.883**	0.465	0.546	0.478
FC_3	0.353	0.448	0.613	**0.876**	0.350	0.541	0.490
FC_5	0.299	0.434	0.634	**0.826**	0.392	0.536	0.555
SI_1	0.285	0.377	0.371	0.358	**0.819**	0.344	0.382
SI_2	0.189	0.356	0.301	0.410	**0.822**	0.297	0.297
SI_3	0.271	0.522	0.387	0.473	**0.906**	0.421	0.356
SI_4	0.364	0.485	0.423	0.481	**0.860**	0.485	0.416
TIIL_ICTM	0.561	0.615	0.570	0.566	0.458	**0.884**	0.549
TIIL_IELL	0.516	0.499	0.537	0.541	0.416	**0.901**	0.476
TIIL_ITEC	0.494	0.486	0.573	0.522	0.373	**0.888**	0.524
UE_EE	0.407	0.456	0.483	0.530	0.477	0.533	**0.889**
UE_PE	0.465	0.516	0.416	0.487	0.297	0.502	**0.894**

Note: Outer loadings of each construct are highlighted in bold.

Table 4 shows the Fornell–Larcker criterion results for UE, SI, FC, CSE, and BTC as second-order constructs. The bolded values on the diagonal in Table 3 represent the square root of all the constructs' AVE and are proved to have greater values than the off-diagonal values representing the correlations between other constructs. Thus, this further supports the establishment of discriminant validity in terms of the Fornell–Larcker criterion.

Table 4. Fornell–Larcker criterion results.

Fornell–Larcker criterion	BI	BTC	CSE	FC	SI	TIIL	UE
BI	**0.909**						
BTC	0.513	**0.785**					
CSE	0.486	0.534	**0.859**				
FC	0.409	0.506	0.728	**0.845**			
SI	0.338	0.521	0.443	0.511	**0.852**		
TIIL	0.589	0.602	0.629	0.610	0.468	**0.891**	
UE	0.489	0.545	0.503	0.570	0.433	0.581	**0.892**

Note: All bolded values on the diagonal represent the square root of all the constructs' AVE; the off-diagonal figures represent the correlations between the constructs.

Table 5 shows the confidence interval for the HTMT results after UE, SI, FC, CSE, and BTC were operationalized as second-order constructs. The results show that the confidence intervals for the HTMT of all constructs are below the threshold of 0.90. This meets the requirement of discriminant validity in terms of the HTMT.

Table 5. Confidence interval for the HTMT results.

HTMT	BI	BTC	CSE	FC	SI	TIIL	UE
BI							
BTC	0.551						
CSE	0.528	0.578					
FC	0.453	0.555	0.829				
SI	0.359	0.559	0.489	0.585			
TIIL	0.652	0.664	0.710	0.698	0.516		
UE	0.588	0.653	0.615	0.709	0.528	0.721	

Note: HTMT < 0.90.

4.2. Structural Model Assessment

Referring to Hair et al. (2017) the structural model assessment includes the following six systematic steps:

Step 1: Assess Collinearity Issues

The tolerance (TOL) and variance inflation factor (VIF) values are two measures used to assess the level of collinearity (Hair et al., 2017). In the context of the PLS-SEM, each predictor construct's tolerance values should exceed 0.2 and the VIF value should be below 5. This indicates that there is no potential collinearity problem for each predictor construct. In Table 6, the columns represent the VIF values of all combinations of endogenous constructs, and the rows explain the corresponding exogenous constructs.

The collinearity assessment was conducted with the following sets of exogenous constructs: (1) UE (1.724), SI (1.559), FC (2.552), CSE (2.317), and BTC (1.802) as predictors of BI; and (2) UE (1.815), SI (1.559), FC (2.557), CSE (2.422), BTC (1.914) and BI (1.564) as predictors of TIIL. Table 6 illustrates that all VIF values are below the threshold of 5.0 and all predictor constructs' TOL values exceed 0.2. This indicates that the predictor constructs' collinearity is not a critical issue. Therefore, the hypothesized structural model is suitable for the next assessment.

Table 6. Collinearity statistics (VIF).

VIF	BI	TIIL
BI		1.564
BTC	1.802	1.914
CSE	2.317	2.422
FC	2.552	2.557
SI	1.559	1.559
UE	1.724	1.815

Step 2: Assess the significant relationships in the structural model

Table 7 displays the direct effect of UE, SI, FC, CSE, BTC, and BI on TIIL. Based on a 0.05 significance level (Hair et al., 2017) the relationships between BI → TIIL, BTC → TIIL, CSE → TIIL, FC → TIIL, and UE → TIIL are significant. The test results report that BI ($p = 0.000$*), BTC ($p = 0.016$*), CSE ($p = 0.002$*), FC ($p = 0.024$*), and UE ($p = 0.033$*) all have a significant effect on TIIL ($p < 0.05$). Conversely, the relationship between SI → TIIL is reported as insignificant ($p > 0.05$). Additionally, based on Hair et al. (2017) if a confidence interval for an estimated path coefficient does not include zero, the path coefficient is assumed to have a significant effect. Otherwise, it is assumed to have a non-significant effect. Thus, it can be concluded from the test results in Table 7 that the five path coefficients that exclude zero (BI → TIIL, BTC → TIIL, CSE → TIIL, FC → TIIL, and UE → TIIL) are significant, whereas the path coefficient for SI → TIIL includes a zero value and is assumed to be insignificant.

Table 7. Direct effect of UE, SI, FC, CSE, BTC and BI on TIIL.

Relationship	Path coefficient (Standard β)	Std. dev.	p-value	95% confidence intervals		Effect size, f^2
				low	up	
BI → TIIL	0.245	0.061	0.000*.	0.120	0.356	0.092
BTC → TIIL	0.179	0.074	0.016*.	0.034	0.323	0.040
CSE → TIIL	0.199	0.063	0.002*.	0.066	0.317	0.038
FC → TIIL	0.161	0.072	0.024*.	0.017	0.300	0.025
SI → TIIL	0.059	0.073	0.421	-0.082	0.203	0.005
UE → TIIL	0.150	0.069	0.033*.	0.015	0.284	0.029

Note: * $p < 0.05$.

Table 8 shows the results for the direct effect of UE, SI, FC, CSE, and BTC on BI. The hypothesis testing results display that the relationships between BTC → BI (0.004), CSE → BI (0.006), and UE → BI (0.004) are highly significant ($p < 0.05$). Conversely, SI (0.903) and FC (0.506) have an insignificant effect on BI ($p > 0.05$) based on the 95% confidence interval value. The path coefficients for BTC → BI, CSE → BI, and UE → BI exclude zero and have a significant effect. Conversely, the path coefficients for SI → BI and FC → BI include zero and have an insignificant effect.

Table 8. Direct effect of UE, SI, FC, CSE, BTC on BI.

Relationship	Path coefficient (Standard β)	Std. dev.	p-value	95% confidence intervals		Effect size, f^2
				Low	Up	
BTC → BI	0.270	0.094	0.004*	0.090	0.458	0.062
CSE → BI	0.252	0.094	0.006*	0.058	0.426	0.045
FC → BI	-0.053	0.084	0.506	-0.216	0.116	0.002
SI → BI	0.008	0.066	0.903	-0.123	0.138	0.000
UE → BI	0.243	0.084	0.004*	0.081	0.412	0.053

Note: * $p < 0.05$

Table 9 shows the results of the significance and relevance of the effects of the mediating relationship: the indirect effect (BTC → BI → TIIL) via mediator BI is significant (p-value = 0.032*); the indirect effect (CSE → BI → TIIL) is significant (p-value = 0.016*); and the indirect effect (UE → BI → TIIL) is significant (p-value = 0.011*). In contrast, the indirect effect (SI → BI → TIIL) is insignificant (p-value = 0.906); and the indirect effect (FC → BI → TIIL) is insignificant (p-value = 0.511). These findings prove that only the mediating effect of BI was supported involving BTC → BI → TIIL, CSE → BI → TIIL, and UE → BI → TIIL. Conversely, the two mediating effects of BI (SI → BI → TIIL and FC → BI → TIIL) are not supported by this research.

Table 9. Mediating effect results.

Indirect effect				Mediating effect		
Path	Std. β	Path	Std. β	Std. β	Std. dev	*p*-value
BTC → BI	0.27	BI-> TIIL	0.245	0.067	0.03	0.032*
CSE → BI	0.252	BI-> TIIL	0.245	0.061	0.027	0.016*
FC → BI	-0.053	BI-> TIIL	0.245	-0.012	0.021	0.511
SI → BI	0.008	BI-> TIIL	0.245	0.002	0.017	0.906
UE → BI	0.243	BI-> TIIL	0.245	0.058	0.023	0.011*

Note: * $p < 0.05$.

Step 3: Assess the level of R^2

The R^2 level is a measure commonly used to evaluate a model's predictive power and ranges from 0 to 1. the higher the R^2 value, the more accurate the model's predictive power. Hair et al. (2017) assert that R^2 values represent substantial (0.26), moderate (0.13), or weak (0.02) predictive powers. Figure 3 shows an R^2 value of 0.587 for construct TIIL, which indicates that UE, SI, FC, CSE, BTC and BI substantially predict TIIL. The R^2 value of 0.361 for the BI construct indicates that UE, SI, FC, CSE, and BTC substantially predict BI in the structural model.

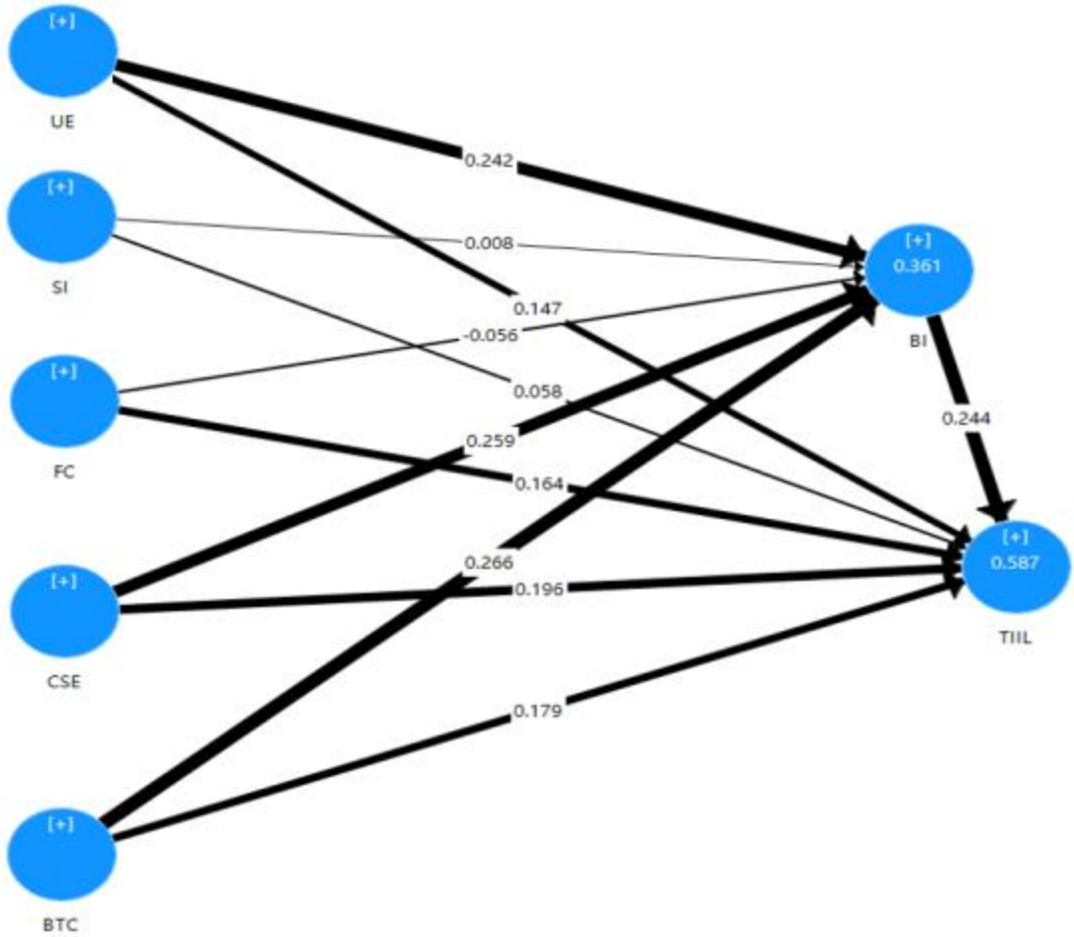

Figure 3. Path model estimation and R^2 values.

Step 4: Assess the Effect Size of f^2

In the current research, the effect size, f^2, assesses the constructs' (i.e., UE, SI, FC, CSE, BTC, and BI) contributions to the TIIL's R^2 value. According to Hair et al. (2017), f^2 values of 0.02, 0.15, and 0.35 indicate that the exogenous construct contributes a small, medium, or large effect on an endogenous construct. Effect size values of less than 0.02 indicate that there is no effect. In Table 7, the f^2 effect size shows that BI (0.092), BTC (0.04), CSE (0.038), FC (0.025), and UE (0.029) have a medium effect on TIIL, while SI (0.005) had no effect. The f^2 effect size displayed in Table 8 show that BTC (0.062), CSE (0.045), and UE (0.053) have a medium-sized effect on BI, whereas FC (0.002) and SI (0.000) have no effect.

Step 5: Assess the Predictive Relevance of Q^2

Hair et al. (2017) asserted that Stone–Geisser's Q^2 value is used to evaluate a model's out-of-sample predictive power or predictive relevance. A Q^2 value above 0 suggests that all exogenous constructs have predictive relevance for the endogenous construct. Conversely, a Q^2 value of 0 and below indicates that the model has no predictive relevance. Current research employs the cross-validated redundancy approach to calculate the Q^2 value. Table 10 shows that the Q^2 values of the two endogenous constructs (TIIL with a Q^2 value of 0.451, and BI with a Q^2 value of 0.288) are above zero. This signifies clear predictive power and predictive relevance.

Table 10. Construct cross-validated redundancy.

Exogenous	Endogenous	Std. β	R^2	Q^2	q^2	Predictive relevance
BTC	BI	0.270**	0.361	0.288	0.048	Yes
CSE		0.252**			0.035	
FC		-0.053			0.003	
SI		0.008			0.001	
UE		0.243**			0.038	
BTC	TIIL	0.245***	0.588	0.451	0.022	Yes
CSE		0.179*			0.024	
FC		0.199**			0.011	
SI		0.161*			0.000	
UE		0.059			0.018	
BI		0.150*			0.055	

Note: Q2 > 0; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Step 6: Assess the q^2 Effect Size

The q^2 effect size assessment is used to assess the contributions of UE, SI, FC, CSE, BTC and BI to the Q^2 values of TIIL and BI. The q^2 values of 0.02, 0.15, and 0.35 show that an exogenous construct has small, medium, or large predictive relevance, respectively, for a particular endogenous construct (Hair et al., 2017). Table 10 shows that the three exogenous constructs of BTC (0.048), CSE (0.035), and UE (0.038) have medium predictive relevance for the endogenous construct (BI), whereas the two exogenous constructs of FC (0.003) and SI (0.001) almost have no predictive relevance for the endogenous construct (BI). Similarly, the q^2 effect size results revealed that three constructs, BTC (0.022), CSE (0.024), and BI (0.055), have medium predictive relevance for TIIL. UE (0.018) has small predictive relevance for TIIL. In contrast, two exogenous constructs, FC (0.001) and SI (0.000), have almost no predictive relevance for TIIL.

5. DISCUSSION

5.1. The Direct Effect of UE, SI, FC, CSE, BTC, and BI on TIIL

This study found that UE positively and significantly affected TIIL, which provides data support for private in-service university teachers to enhance their job performance to develop their informatization instructional leadership in the future. The new empirical evidence benefits private universities regarding the improvement of education technology, teaching management platforms, and digital tools to make them easy to use with the purpose of motivating university teachers to actively adopt information technology to lead blended teaching. This discovery is line with a study by Venkatesh et al. (2003) in which the relationship between performance expectancy and behavior is perceived from outcome expectations based on social cognitive theory. Additionally, the new extended UTAUT theoretical model in this study with direct relationships between performance expectancy and use behavior, and between effort expectancy and use behavior will contribute to teachers' beliefs that they are willing to perform certain use behavior if they exert less effort and easily use a digital device/teaching management platform/technology. In addition, policymakers in charge of university teachers' professional development and instructional leadership training can encourage teachers to engage in informatization instructional leadership through supporting feasible performance expectancy and easy technology to operate.

The new empirical finding that social influence positively affects TIIL indicates the higher social influence, the higher teachers' informatization instructional leadership. However, it was found to be non-significant between SI and TIIL. This is because of the presence of BI as a mediator, weakening the direct significant effect of SI on TIIL in the hypothesized structural model. Beyond that, this new extended UTAUT theoretical model in the current study with the direct relationships between social influence and use behavior indicates that a university teacher perceives social pressure (such as peer pressure, supervisory pressure, or faculty motivation) as having no effect on the individual adoption of a new technology/device/tool in teachers' instructional leadership.

The findings show that the direct effect of FC on TIIL is positive and significant, indicating when the facilitating conditions for adopting TIIL are high, teachers' TIIL behavior is also high. Furthermore, facilitating conditions have a significant effect on TIIL. These findings further support the UTAUT in which FC is a direct determinant of technology use behavior. When the in-service teachers strongly believe that they are provided with a sufficient environment or policy support, they will be facilitated in adopting TIIL behavior. This finding is supported by Perera and Abeysekera (2019); Raman and Thannimalai (2021) and Yeop, Yaakob, Wong, Don, and Zain (2019) who found that facilitating conditions had a significant influence on the use behavior of technology.

This research found that computer self-efficacy has a positive and significant effect on TIIL among in-service teachers. This indicates that the higher CSE that in-service teachers possess, the greater the TIIL they will show. This is in accordance with the current research finding that one's self-efficacy is correlated with their leadership behavior (Alanoglu, 2022; Liu & Hallinger, 2018; Papaioannou, Papavassiliou-Alexiou, & Moutiaga, 2022). The new theoretical model generated from this study is the extended UTAUT model with direct relationships between computer self-efficacy and use behavior. The new model will contribute to teachers' belief that they will actively carry out certain use behavior if they focus on developing better computer self-efficacy. In addition, this serves as a reminder to policymakers to pay attention to teachers' computer self-efficacy.

The new discovery in current research reveals that the direct effect of blended teaching competence on TIIL among in-service teachers is positive and significant. This indicates that the higher the blended teaching competence that in-service teachers possess, the greater their adoption of TIIL will become. Furthermore, the relationship between blended teaching competence and TIIL is found to be significant. This result is supported by the theory of planned behavior in which blended teaching competence can be used to measure TIIL. In addition, this result also confirms an emerging study by Zhao (2019) suggesting that teachers' blended teaching competency is one of the important influencing factors in predicting teachers' informatization teaching leadership. Additionally, the new extended UTAUT model contributes to teachers' belief that they will actively perform certain use behavior if they focus on improving their blended teaching competence. Therefore, policymakers should pay attention to teachers' blended teaching competence.

The new discovery that BI positively and significantly impacts TIIL is consistent with UTAUT and TPB, identifying that BI is both an exogenous variable and an endogenous variable, which is a predictor of an individual's use behavior. This discovery is another contribution of this empirical research to the domain of educational management. Additionally, the new model contributes to teachers' belief that they will actively perform certain use behavior if they have a strong intention to use a certain technology. This reminds policymakers to pay attention to teachers' behavioral intentions.

5.2. The Direct Effect of UE, SI, FC, CSE, BTC on BI

The research finding that UE shows a positive and significant effect on BI toward TIIL among in-service teachers indicates the higher the use expectancy, the greater the BI toward TIIL. This further supports the theory of the Technology Acceptance Model by Davis (1989) in which he stated that ease of use and perceived usefulness determine one's behavioral intention to adopt information technology. This new discovery is consistent with the corresponding study proposed by past studies (Fobang, Wamba, & Kamdjoug, 2019; Perera & Jayawardana, 2022; Sair & Danish, 2018; Tamrakar & Shrestha, 2022). In addition, the new discovery made by the current study will contribute to teachers' belief that strong behavioral intention to use informatization instructional leadership will produce good performance expectancy, and that effort expectancy will help teachers to produce the behavioral intention to adopt informatization instructional leadership. This can remind policymakers to pay attention to performance expectancy and effort expectancy.

The empirical evidence shows that social influence had a positive but insignificant effect on BI toward TIIL, which supports previous research by Jameel, Abdalla, and Karem (2020) who found that SI insignificantly affected

BI in the educational context. However, this finding is not in alignment with some emerging studies which found that SI had a significant impact on behavioral intention and played an important role in increasing behavioral intention (Salloum & Shaalan, 2019; Tarhini et al., 2017). This discovery will contribute to policymaking in relation to teachers' training for improving teachers' informatization leadership.

FC showed a positive but insignificant effect on BI toward TIIL among in-service teachers. This clearly indicates that the higher FC, the lower the BI toward TIIL among in-service teachers, and this is inconsistent with the research by Baydas and Goktas (2017) who found that poor facilitating conditions negatively influenced technology use among English teachers in China, including inadequate technical support and technology training. Conversely, however, this finding further supports the original UTAUT model by Venkatesh et al. (2003) that FC has no influence on the intention to use information technology. Practically, this finding indicates that in-service teachers consider technology facilities that the organization provide as not affecting an individual's adoption of a new technology/device/tool in teachers' instructional leadership.

The discovery that computer self-efficacy has a positive and significant effect on BI toward TIIL indicates that the higher the CSE that in-service teachers have, the more BI to adopt TIIL they will show. Greater computer self-efficacy will help in-service teachers to positively deal with complex and difficult education technology in their teaching leadership and management. Current research findings are in accordance with the Social Cognitive Theory by Bandura (1986) in which he posited computer self-efficacy as an individual's assessment of his/her capability to use a computer. The new UTAUT model extended with the direct relationship between CSE and BI will contribute to teachers' belief that they will have enough intention to adopt TIIL if they focus on improving their computer self-efficacy. This reminds policymakers to pay attention to teachers' computer self-efficacy.

Blended teaching competence showed a positive and significant effect on behavioral intention toward TIIL, which is a new research discovery of the UTAUT model applied in the field of informatization instructional leadership. This clearly suggests that if in-service teachers possess higher blended teaching competence, they will usually have a greater intention toward TIIL. The new model contributes to teachers' belief that they will have the intention to carry out TIIL if they improve their blended teaching competence. In addition, this can remind policymakers to pay attention to teachers' blended teaching competence.

5.3. Behavioral Intention Mediating Relationships Between UE, SI, FC, CSE, BTC and TIIL

This empirical finding has proved that use expectancy has a positive and significant effect on TIIL, with behavioral intention as a mediator. The finding further confirms many studies that also found behavioral intention to be a mediator of the indirect effect of use expectancy on use behavior (Attuquayefio & Addo, 2014; Bervell & Umar, 2017; Tseng et al., 2022). In addition, it supports the theory of the Technology Acceptance Model, which posits that intention has a significant mediating effect on use expectancy and use behavior. This positive behavioral intention not only leads to positive feelings but also increases teachers' job performance. They are more willing to invest time and effort to ensure positive job performance. Practically, this new discovery helps university teachers to develop their behavioral intention to apply TIIL. Therefore, policymakers should focus on teachers' behavioral intention to use educational technology to lead and manage blended teaching.

The research discovery from the data analysis that behavioral intention does not mediate the relationship between social influence and TIIL clearly indicates that SI has not a positive and significant effect on TIIL by BI as a mediator. The finding is inconsistent with many researches in which they justified the mediating effect of BI between SI and use behavior (Attuquayefio & Addo, 2014; Bervell & Umar, 2017; Raman & Don, 2013; Tseng et al., 2022). This new discovery is inconsistent with the UTAUT by Venkatesh et al. (2003) who stated that behavioral intention mediates SI and TIIL. Similarly, this new discovery is inconsistent with the TPB in which intention mediates the relationship between subjective norms and behavior. The rationale behind this is that the UTAUT is applied in the field of educational management and leadership processes compared with the usual application of the

UTAUT in the teaching process in the educational context.

The research result that behavioral intention does not mediate the relationship between FC and TIIL is not in accordance with some research that justified the indirect influence of BI as a mediator between FC and use behavior (Alyoussef, 2021; Tseng et al., 2022). This new finding supports the UTAUT which shows that FC directly predicts use behavior but isn't mediated through BI. This is due to the application of the UTAUT model in the educational management field compared with the UTAUT model applied in the teaching field in an education context.

The finding that behavioral intention mediates the relationship between computer self-efficacy and TIIL further confirms the theory of planned behavior by Ajzen (1991) who stated that the influence of perceived behavioral control (PBC) on behavior is mediated through intention. Computer self-efficacy impacts behavior with behavioral intention as a mediator. This reminds policymakers to pay attention to the importance of behavioral intention as a mediator.

The new discovery that BI mediates the relationship between blended teaching competence and TIIL clearly proves that in order to account for the adoption of TIIL, a teacher has to change his/her behavioral intention. Teachers with positive BI will have a stronger desire to adopt TIIL. University teachers with high BTC will have a stronger BI to adopt TIIL. This positive BI not only leads to positive feelings but also increases teachers' desire to improve BTC. They become less critical when they encounter difficulties using educational technology in instructional leadership. They are also willing to invest time and effort to study computer technology to improve their blended teaching competence. This new discovery further expands the UTAUT model into educational management and helps university teachers to improve the practical competence of informatization instructional leadership. Additionally, this can remind policymakers to pay attention to teachers' blended teaching competence.

6. CONCLUSION

Teachers' informatization instructional leadership is contributed to by many variables—use expectancy, facilitating conditions, computer self-efficacy, blended teaching competence, and behavioral intention. Teachers' behavioral intention to adopt technology in instructional leadership is directly influenced by use expectancy, computer self-efficacy and blended teaching competence. Furthermore, UE, CSE, and BTC indirectly influence the use of TIIL through the mediating variable of BI.

The proposed extended UTAUT in this study is a new and crucial milestone toward the convergence of research in the scope of teachers' instructional leadership. On this basis, efforts to develop TIIL should consider all of these contributing factors. The results indicate the most important contribution and underscore the importance of emphasizing these contributing factors in the domain of informatization educational leadership. This study has shown that university teachers' professional development and training with the application of TIIL will develop innovative, competitive, collaborative and technology-based competencies.

7. IMPLICATIONS OF THE RESEARCH FINDINGS

The current empirical findings contribute to preliminary research pertaining to teachers' instructional leadership and management, educators undertaking university teacher training programs, and policymakers regarding teachers' educational assessment in the Chinese Ministry of Higher Education (CMHE). The proposed structural model enriches the theoretical and model development in the field of TIIL. It provides theoretical reference for university policymakers to develop teacher training programmes that focus on two variables (computer self-efficacy and blended teaching competence) and boost teachers' behavioral intention as a mediator to apply TIIL. Studies that address the more complex constructs with consistent moderating effects integrated with new variables are scarce. The current study also contributes to research methodology related to PLS-SEM in times of educational digitization compared with using a first-generation statistical multivariate regression analysis to understand the relationships between the variables hypothesized (Zhao, 2019). However, this research employed a second-generation statistical approach (PLS-SEM technique) simultaneously to analyze first-order and second-order constructs which fit into a more complex structural model. Practically, the teacher development body assesses teacher informatization instructional leadership by focusing more on the development of use expectancy (i.e., performance expectancy and effort expectancy), facilitating conditions, computer self-efficacy, blended teaching competence instead of only concentrating on the pedagogy and content knowledge delivery skills.

Funding: This study received no specific financial support.
Institutional Review Board Statement: The Ethical Committee of the Faculty of Psychology and Education, University Malaysia Sabah, Malaysia has granted approval for this study on 25 September 2023 (Ref. No. DP1921112A).
Transparency: The authors state that the manuscript is honest, truthful, and transparent, that no key aspects of the investigation have been omitted, and that any differences from the study as planned have been clarified. This study followed all writing ethics.
Competing Interests: The authors declare that they have no competing interests.
Authors' Contributions: Contributed to the conceptualization, validation, formal analysis, investigation, data curation, writing (original draft) preparation, and visualization, W.L.; contributed to the methodology, software, resources, writing review and editing, supervision, and project administration, Y.F.L. Both authors have read and agreed to the published version of the manuscript.

REFERENCES

Ain, N., Kaur, K., & Waheed, M. (2016). The influence of learning value on learning management system use: An extension of UTAUT2. *Information Development, 32*(5), 1306-1321. https://doi.org/10.1177/0266666915597546

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50*(2), 179-211.

Alanoglu, M. (2022). The role of instructional leadership in increasing teacher self-efficacy: A meta-analytic review. *Asia Pacific Education Review, 23*(2), 233-244. https://doi.org/10.1007/s12564-021-09726-5

Alyoussef, I. Y. (2021). Factors influencing students' acceptance of M-learning in higher education: An application and extension of the UTAUT model. *Electronics, 10*(24), 3171. http://doi.org/10.3390/electronics10243171

Ameri, A., Khajouei, R., Ameri, A., & Jahani, Y. (2020). Acceptance of a mobile-based educational application (LabSafety) by pharmacy students: An application of the UTAUT2 model. *Education and Information Technologies, 25*(1), 419-435. https://doi.org/10.1007/s10639-019-09965-5

Attuquayefio, S., & Addo, H. (2014). Using the UTAUT model to analyze students' ICT adoption. *International Journal of Education and Development using ICT, 10*(3), 75-86.

Bandura, A. (1986). *Social foundations of thought and action: A social cognitive theory*. Englewood Cliffs, NJ: Prentice-Hall.

Baydas, O., & Goktas, Y. (2017). A model for preservice teachers' intentions to use ICT in future lessons. *Interactive Learning Environments, 25*(7), 930-945. https://doi.org/10.1080/10494820.2016.1232277

Bervell, B., & Umar, I. N. (2017). Validation of the UTAUT model: Re-considering non-linear relationships of exogeneous variables in higher education technology acceptance research. *Eurasia Journal of Mathematics, Science and Technology Education, 13*(10), 6471-6490. https://doi.org/10.12973/ejmste/78076

Chinese Ministry of Education. (2022). *Ministry of education of the people's Republic of China*. Retrieved from https://so.moe.gov.cn/s?siteCode=bm05000001&tab=all&qt202212.24

Chua, Y. P., & Chua, Y. P. (2017). How are e-leadership practices in implementing a school virtual learning environment enhanced? A grounded model study. *Computers & Education, 109*, 109-121. https://doi.org/10.1016/j.compedu.2017.02.012

Compeau, D., & Higgins, C. (1995). Computer self-efficacy: Development of a measure and initial test. *MIS Quarterly, 19*(2), 189-211. https://doi.org/10.2307/249688

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319-340. https://doi.org/10.2307/249008

Ellis, R. A., Goodyear, P., O'Hara, A., & Prosser, M. (2007). The university student experience of face-to-face and online discussions: Coherence, reflection and meaning. *Association of Learning Technology Journal*, *15*(1), 83-97. https://doi.org/10.1080/09687760601130057

Feng, X., Wang, R., & Wu, Y. (2018). A literature review on blended learning: Based on analytical framework of blended learning. *Journal of Distance Education*, *3*, 13-24. https://doi.org/10.15881/j.cnki.cn33-1304/g4.2018.03.002

Fobang, N. A., Wamba, F. S., & Kamdjoug, K. J. R. (2019). Exploring factors affecting the adoption of HRIS in SMEs in a developing country: Evidence from Cameroon. *Technologies on Organizations and Society*, *30*, 281-295. https://doi.org/10.1007/978-3-030-10737-6_18

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017). *A primer on partial least squares structural equation modelling (PLS-SEM)* (2nd ed.). United States of America: SAGE Publication.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*, 115-135. https://doi.org/10.1007/s11747-014-0403-8

Ifedayo, A. E., Ziden, A. A., & Ismail, A. B. (2021). Mediating effect of behavioural intention on podcast acceptance. *Education and Information Technologies*, *26*, 2767-2794. https://doi.org/10.1007/s10639-020-10385-z

Jaipal-Jamani, K., Figg, C., Collier, D., Gallagher, T., Winters, K.-L., & Ciampa, K. (2018). Developing TPACK of university faculty through technology leadership roles. *Italian Journal of Educational Technology*, *26*(1), 39-55.

Jameel, A. S., Abdalla, S. N., & Karem, M. A. (2020). *Behavioural intention to use e-learning from student's perspective during COVID-19 Pandemic*. Paper presented at the 2nd Annual International Conference on Information and Sciences (AiCIS) IEEE.

Kaboodvand, T. (2020). Influence of facilitating condition, school ICT leadership and computer self efficacy on students' ICT engagement for learning mathematics among secondary mathematics students in Iran-Zanjan. *International Research Journal of Education and Sciences*, *4*(1), 28-33.

Kang, M., Liew, B. Y. T., Lim, H., Jang, J., & Lee, S. (2015). Investigating the determinants of mobile learning acceptance in Korea using UTAUT2. In Emerging issues in smart learning. In (pp. 209-216). Berlin Heidelberg: Springer.

Karsten, R., Mitra, A., & Schmidt, D. (2012). Computer self-efficacy: A meta-analysis. *Journal of Organizational and End User Computing*, *24*(4), 54-80. https://doi.org/10.4018/joeuc.2012100104

Li, Y. F. (2020b). Research on influencing factors and forming path of informatization leadership behavior of primary school teachers. *Education Research*, *41*(4), 109-115. https://doi.org/10.13811/j.cnki.eer.2020.04.015

Lin, C.-Y., Huang, C.-K., & Ko, C.-J. (2020). The impact of perceived enjoyment on team effectiveness and individual learning in a blended learning business course: The mediating effect of knowledge sharing. *Australasian Journal of Educational Technology*, *36*(1), 126-141. https://doi.org/10.14742/ajet.4446

Liu, S., & Hallinger, P. (2018). Principal instructional leadership, teacher self-efficacy, and teacher professional learning in China: Testing a mediated-effects model. *Educational Administration Quarterly*, *54*(4), 501-528. https://doi.org/10.1177/0013161x18769048

Marakas, G., Johnson, R., & Clay, P. F. (2007). The evolving nature of the computer self-efficacy construct: An empirical investigation of measurement construction, validity, reliability and stability over time. *Journal of the Association for Information Systems*, *8*(1), 2. https://doi.org/10.17705/1jais.00112

Mikalef, P., Pappas, I. O., & Giannakos, M. (2016). An integrative adoption model of video-based learning. *The International Journal of Information and Learning Technology*, *33*(4), 219-235. https://doi.org/10.1108/ijilt-01-2016-0007

Nandwani, S., & Khan, S. (2016). Teachers' intention towards the usage of technology: An investigation using UTAUT model. *Journal of Education & Social Sciences*, *4*(2), 95-111. https://doi.org/10.20547/jess0421604202

Papaioannou, A., Papavassiliou-Alexiou, I., & Moutiaga, S. (2022). Career resilience and self-efficacy of Greek primary school leaders in times of socioeconomic crisis. *International Journal of Educational Management*, *36*(2), 164-178. https://doi.org/10.1108/ijem-01-2021-0024

Park, S. H. S., Lee, L., & Yi, M. Y. (2011). Group-level effects of facilitating conditions on individual acceptance of information systems. *Information Technology and Management*, *12*, 315-334. https://doi.org/10.1007/s10799-011-0097-2

Perera, A. H. U., & Jayawardana, A. K. L. (2022). The impact of charismatic leadership and computer self-efficacy on HRIS user acceptance and HRIS use behaviour. *Sir Lankan Journal of Management*, *27*(1), 29-39.

Perera, H. U., & Abeysekera, N. (2019). The role of charismatic leadership and computer self efficacy on information system user acceptance and use behaviour: A conceptual framework. *Sri Lankan Journal of Management*, *24*(1), 105-120.

Prasad, P., Maag, A., Redestowicz, M., & Hoe, L. S. (2018). Unfamiliar technology: Reaction of international students to blended learning. *Computers & Education*, *122*, 92-103. https://doi.org/10.1016/j.compedu.2018.03.016

Pulham, E., & Graham, C. R. (2018). Comparing K-12 online and blended teaching competencies: A literature review. *Distance Education*, *39*(3), 411-432. https://doi.org/10.1080/01587919.2018.1476840

Radovan, M., & Kristl, N. (2017). Acceptance of technology and its impact on teacher's activities in virtual classroom: Integrating UTAUT and CoI into a combined model. *Turkish Online Journal of Educational Technology*, *16*(3), 11-22. https://doi.org/10.1109/asiancon58793.2023.10270575

Raman, A., & Don, Y. (2013). Preservice teachers' acceptance of learning management software: An application of the UTAUT2 model. *International Education Studies*, *6*(7), 157-164. https://doi.org/10.5539/ies.v6n7p157

Raman, A., & Thannimalai, R. (2019). Importance of technology leadership for technology integration: Gender and professional development perspective. *Sage Open*, *9*(4), 1-13. https://doi.org/10.1177/2158244019893707

Raman, A., & Thannimalai, R. (2021). Factors impacting the behavioural intention to use e- learning at higher education amid the Covid-19 pandemic: UTAUT2 model. *Psychological Science & Education*, *26*(3), 82-93. https://doi.org/10.17759/pse.2021260305

Sair, S. A., & Danish, R. Q. (2018). Effect of performance expectancy and effort expectancy on the mobile commerce adoption intention through personal innovativeness among Pakistani consumers. *Pakistan Journal of Commerce and Social Sciences*, *12*(2), 501-520.

Salloum, S. A., & Shaalan, K. (2019). *Factors affecting students' acceptance of e-learning system in higher education using UTAUT and structural equation modeling approaches*. Paper presented at the Proceedings of the International Conference on Advanced Intelligent Systems and Informatics 2018 4.

Tamrakar, B., & Shrestha, A. (2022). Factors influencing use of human resource information system in Nepali organizations. *Journal of Business and Management Research*, *4*(01), 1-16. https://doi.org/10.3126/jbmr.v4i01.46678

Tarhini, A., Masa'deh, R. e., Al-Busaidi, K. A., Mohammed, A. B., & Maqableh, M. (2017). Factors influencing students' adoption of e-learning: A structural equation modeling approach. *Journal of International Education in Business*, *10*(2), 164-182. https://doi.org/10.1108/jieb-09-2016-0032

Teo, T., Huang, F., & Hoi, C. K. W. (2018). Explicating the influences that explain intention to use technology among English teachers in China. *Interactive Learning Environments*, *26*(4), 460-475. https://doi.org/10.1080/10494820.2017.1341940

Testa, N., & Tawfik, A. (2017). Mobile, but are we better? Understanding teacher's perception of a mobile technology integration using the unified theory of acceptance and use of technology (UTAUT) framework. *Journal of Formative Design in Learning*, *1*(2), 73-83. https://doi.org/10.1007/s41686-017-0010-4

Thannimalai, R., & Raman, A. (2018). The influence of principals' technology leadership and professional development on teachers' technology integration in secondary schools. *Malaysian Journal of Learning and Instruction*, *15*(1), 201-226. https://doi.org/10.32890/mjli2018.15.1.8

Thongsri, N., Shen, L., Bao, Y., & Alharbi, I. M. (2018). Integrating UTAUT and UGT to explain behavioural intention to use M-learning: A developing country's perspective. *Journal of Systems and Information Technology*, *20*(3), 278-297. https://doi.org/10.1108/jsit-11-2017-0107

Tseng, T. H., Lin, S., Wang, Y.-S., & Liu, H.-X. (2022). Investigating teachers' adoption of MOOCs: The perspective of UTAUT2. *Interactive Learning Environments*, *30*(4), 635-650. https://doi.org/10.1080/10494820.2019.1674888

Valtonen, T., Kukkonen, J., Kontkanen, S., Sormunen, K., Dillon, P., & Sointu, E. (2015). The impact of authentic learning experiences with ICT on pre-service teachers' intentions to use ICT for teaching and learning. *Computers & Education*, *81*, 49-58. https://doi.org/10.1016/j.compedu.2014.09.008

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science*, *46*(2), 186-204. https://doi.org/10.1287/mnsc.46.2.186.11926

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

Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *Management Information Systems Quarterly*, *36*(1), 157-178. https://doi.org/10.2307/41410412

Yang, Y., Zhang, H., Chai, H., & Xu, W. (2022). Design and application of intelligent teaching space for blended teaching. *Interactive Learning Environments*, 1-18. https://doi.org/10.1080/10494820.2022.2028857

Yeop, M. A., Yaakob, M. F. M., Wong, K. T., Don, Y., & Zain, F. M. (2019). Implementation of ICT policy (Blended Learning Approach): Investigating factors of behavioural intention and use behaviour. *International Journal of Instruction*, *12*(1), 767-782. https://doi.org/10.29333/iji.2019.12149a

Zh, S. X., & Liu, X. C. (2015). Teachers' informatization instructional leadership: Concept, connotation and investigation and analysis. *Modern Distance Education*(4), 28-36. https://doi.org/10.13927/j.cnki.yuan.2015.0041

Zh, S. X., & Zhang, D. Q. (2016). Study on generation mechanism of teachers' informatization leadership: Based on an analysis of environmental theory. *Journal of Distance Education*, *2016*(5), 105-112. https://doi.org/10.15881/j.cnki.cn33-1304/g4.2016.05.012

Zh, Y. T., & Zhang, X. F. (2020). Impact of teachers' information technology leadership on teaching efficacy: An empirical analysis using structural equation model. *Teacher Education Research*, *32*(2), 48-56. https://doi.org/10.13445/j.cnki.t.e.r.2020.02.008

Zhao, L. (2019). Teachers' informationization teaching leadership: Connotation, influencing factors and improving path. *Chongqing Higher Education Research*, 7(3), 86-97.

Zhu, L. F., & Zhang, X. Y. (2019). From the perspective of information teaching leadership: How to improve teachers' teaching efficacy. *Journal of Qiqihar Junior Teachers' College*(1), 23-24. https://doi.org/10.16322/j.cnki.23-1534/z.2019.01.008