

Exploration of the Interplay Between Perceived Usefulness, Perceived Ease of Use, Facilitating Conditions, Computer Self-Efficacy, Instructor Efficiency, and Behavioral Intention to Distance Learning

Yan Zeng^{1,2}, Siok Peh Seah^{1*}, Xuanyun Wang^{1,3}

¹Faculty of Education and Liberal Studies, City University Malaysia, 46100 Petaling Jaya, Selangor, Malaysia

²School of Information Engineering, Mianyang Teachers' College, Mianyang 621000, Sichuan Province, China

³Sichuan College of Traditional Chinese Medicine, Mianyang 621000, Sichuan Province, China

*Corresponding author: Siok Peh Seah, sp_seah@fpm.upsi.edu.my

Copyright: © 2024 Author(s). This is an open-access article distributed under the terms of the Creative Commons Attribution License (CC BY 4.0), permitting distribution and reproduction in any medium, provided the original work is cited.

Abstract: This study explores the acceptance of educational support technologies in distance learning within a Chinese higher education context. It examines the influence of perceived usefulness, perceived ease of use, facilitating conditions, computer self-efficacy, and instructor efficiency on students' behavioral intention toward distance learning. Utilizing a quantitative approach with surveys and structural equation modeling, data from 720 participants at Mianyang Teachers' College, China, were analyzed. The findings reveal significant positive effects of these factors on the intention to engage in distance learning, offering valuable insights for enhancing technology acceptance in educational settings.

Keywords: Distance learning; Perceived usefulness; Perceived ease of use; Facilitating conditions; Computer self-efficacy; Instructor efficiency; Behavioral intention

Online publication: June 20, 2024

1. Introduction

In recent years, Open and Distance Learning (ODL) has witnessed a surge in popularity within the higher education field in China. This transformation is driven by various factors, including the increased demand for university education, challenges related to overcrowded residential facilities, and the growing need for advanced learning opportunities ^[1]. The rapid global development of information and communication technologies (ICT) has played a pivotal role in reshaping the education landscape, prompting substantial investments in technical infrastructure by educational institutions ^[2]. This article explores the impact of technology on the evolution of Open and Distance Learning in China, examining how institutions are adapting to paradigm shifts and integrating technology into their curriculum to address contemporary challenges.

2. Problem statement

In recent years, educational institutions, including Mianyang Teachers' College, have invested significantly in modern technology, ensuring access to up-to-date computers, and internet connectivity. The intention is to leverage technology seamlessly in teaching and learning processes, aligning with pedagogical principles, attitudes, curriculum requirements, and available physical facilities [3]. However, despite the widespread recognition of the importance of technology, adoption and usage issues persist, impacting both traditional and alternative (open) educational systems [4].

Data and statistics from prior studies indicate the prevalence of challenges in technology adoption [5]. However, limited research, particularly with a theoretical foundation, has been conducted on the impact of Chinese teachers and trainers on students' learning and the effective use of technology in ODL [6].

By addressing this research gap, this study aims to contribute to the literature by providing an in-depth examination of the factors influencing the acceptance of educational support technologies in distance learning programs at Mianyang Teachers' College, China, utilizing a comprehensive theoretical framework.

In order to better study this problem, the following research hypotheses are proposed in this study:

- (1) H1: Perceived usefulness will have a positive effect on behavioral intention to distance learning.
- (2) H2: Perceived ease of use will have a positive effect on behavioral intention to distance learning.
- (3) H3: Facilitating conditions will have a positive effect on behavioral intention to distance learning.
- (4) H4: Computer self-efficacy will have a positive effect on behavioral intention to distance learning.
- (5) H5: Instructor efficiency will have a positive effect on behavioral intention to distance learning.

3. Conceptual framework

Based on the document search, the following research framework was established (**Figure 1**).

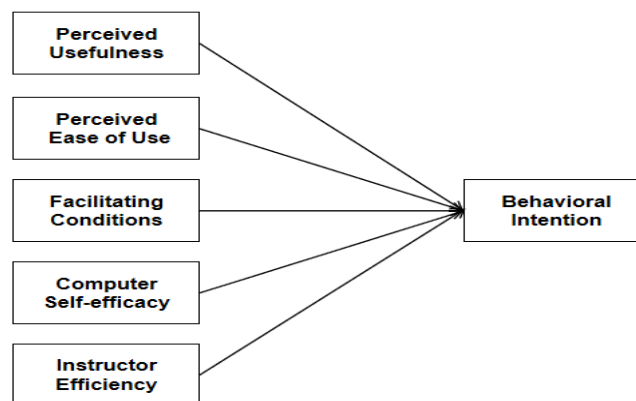


Figure 1. Conceptual framework

4. Methodology

This research used a systematic way to examine university students' adoption of educational support technology in remote learning programs at Mianyang Teachers' College, China. This chapter covers the research approach, philosophy, site, design, operationalization, data collection methods, population and sample, survey tools, data analysis methodologies, and validity and reliability.

The research method was quantitative. This method quantifies the phenomenon using numerical data, supporting deductive reasoning. The quantitative approach measures factors and uses statistical analysis to

generate generalizable conclusions about educational technology acceptability.

This research was done at Mianyang Teachers' College in China. This venue was chosen strategically to study technological adoption in Chinese higher education. As a model case study, Mianyang Teachers' College can offer insights into similar educational institutions.

The main data collection method was structured survey questionnaires. This method efficiently collects quantitative data from a big sample. The surveys collect participants' views, attitudes, and actions on educational support technology use in distance learning programs.

5. Research design

This study prepared to use the method of quantitative research to collect data through questionnaires and analyze the data through the PLS-SEM to seek the relationship between perceived usefulness, perceived ease of use, facilitating conditions, computer self-efficacy, instructor efficiency, and behavioral intention to distance learning.

6. Results

774 people completed the initial survey. Trimming out disengaged responses ensured data precision. This process eliminated uniform responses (such as rating all Likert scale items the same) and inconsistent responses. After excluding unengaged respondents, the dataset had 720 valid responses, 93% of the initial responses.

After checking for variable and dataset collinearity, the study tested hypotheses. A one-tailed significance test was used to assess five positive direct-effect hypotheses. Hypothesis testing used the bootstrap method with 10,000 resamplings. The following theories were tested: Hypotheses 1–5 examined how perceived usefulness, perceived ease of use, facilitating conditions, computer self-efficacy, and instructor efficiency affect remote learning behavior.

Table 1 shows indicator loadings, Cronbach's alpha (CA), composite reliability (CR) values, and average variance extracted (AVE) values for convergent validity. All measurement indicators for each variable have loadings above 0.7. According to Hair *et al.* [7], ideal indicator loadings should surpass 0.7, however, loadings from 0.40 to 0.69 are acceptable if they do not compromise internal consistency reliability and convergent validity. All measurement items for each variable have substantial indicator loadings for variable measurement in this study, ranging from 0.718 to 0.889.

Table 1. Measurement model for reliability and validity

Dimension	Items	Loading	CA	CR	AVE
BI	BI1	0.856	0.872	0.912	0.722
	BI2	0.889			
	BI3	0.829			
	BI4	0.823			
CSE	CSE1	0.760	0.849	0.892	0.624
	CSE2	0.816			
	CSE3	0.812			
	CSE4	0.786			
	CSE5	0.774			

Table 1 (Continued)

Dimension	Items	Loading	CA	CR	AVE
FC	FC1	0.837	0.822	0.882	0.653
	FC2	0.802			
	FC3	0.820			
	FC4	0.770			
IE	IE1	0.813	0.840	0.887	0.610
	IE2	0.772			
	IE3	0.818			
	IE4	0.718			
	IE5	0.781			
PEU	PEU1	0.811	0.875	0.909	0.667
	PEU2	0.868			
	PEU3	0.817			
	PEU4	0.782			
	PEU5	0.803			
PU	PU1	0.827	0.880	0.912	0.675
	PU2	0.812			
	PU3	0.834			
	PU4	0.802			
	PU5	0.830			

Abbreviation: Perceived usefulness (PU), perceived ease of use (PEU), facilitating conditions (FC), computer self-efficacy (CSE), instructor efficiency (IE), behavioral intention to distance learning (BI)

This study used Cronbach's alpha and composite reliability to determine internal consistency reliability. According to Hair *et al.* [7], composite reliability gives slightly higher values than Cronbach's alpha, which is cautious. Reporting both values is prudent since they provide a more complete dependability assessment. Despite their different underestimating and overestimating tendencies, both approaches use 0.60. Values below this threshold indicate poor internal consistency. This study found that Cronbach's alpha and composite reliability scores exceeded 0.60, ranging from 0.822 to 0.912. This shows that study variables are internally consistent.

This study evaluates convergent validity using AVE for each variable. Hair *et al.* [7] recommended an AVE value over 0.50 to ensure that measurement indicators for each variable converge and accurately measure the variable. **Table 1** shows that the AVE values of all variables surpass 0.5, ranging from 0.610 to 0.722. These results indicate good convergent validity for model variables.

This study also used the Heterotrait-Monotrait (HTMT) correlation ratio to assess discriminant validity. In **Table 2**, HTMT ratios are calculated for each dimension pair. The HTMT ratio discriminant validity threshold is 0.85, according to Henseler *et al.* [8]. The HTMT values show that all ratios are below this threshold, supporting discriminant validity across all dimensions. The HTMT analysis confirms the measurement model's discriminant validity, proving that the study's constructs are differentiated. This conclusion strengthens their unique representation in the study framework.

Table 2. Heterotrait-Monotrait ratio (HTMT)

	BI	CSE	FC	IE	PEU	PU
BI						
CSE	0.549					
FC	0.732	0.599				
IE	0.698	0.558	0.681			
PEU	0.690	0.635	0.786	0.672		
PU	0.668	0.554	0.649	0.623	0.756	

Abbreviation: Perceived usefulness (PU), perceived ease of use (PEU), facilitating conditions (FC), computer self-efficacy (CSE), instructor efficiency (IE), behavioral intention to distance learning (BI)

Table 3 delineates the outcomes of the direct effect hypothesis testing conducted in the study. These results indicate that all five examined predictors—perceived usefulness (PU), perceived ease of use (PEU), facilitating conditions (FC), computer self-efficacy (CSE), and instructor efficiency (IE)—exert a significant influence on the behavioral intention towards distance learning (BI). Specifically, the analysis yielded the following associations: PU to BI ($\beta = 0.198$, $P < 0.05$), PEU to BI ($\beta = 0.130$, $P < 0.05$), FC to BI ($\beta = 0.256$, $P < 0.05$), CSE to BI ($\beta = 0.063$, $P < 0.05$), and IE to BI ($\beta = 0.243$, $P < 0.05$). Consequently, hypotheses 1 to 5 are empirically supported.

Table 3. Path coefficients for direct effects

Hypothesis	Direct effect	Beta	SE	<i>t</i> statistics	<i>P</i> value	Result
H1	PU → BI	0.198	0.040	4.913	0.000	Supported
H2	PEU → BI	0.130	0.051	2.544	0.005	Supported
H3	FC → BI	0.256	0.050	5.140	0.000	Supported
H4	CSE → BI	0.063	0.033	1.948	0.026	Supported
H5	IE → BI	0.243	0.053	4.550	0.000	Supported

Abbreviation: Perceived usefulness (PU), perceived ease of use (PEU), facilitating conditions (FC), computer self-efficacy (CSE), instructor efficiency (IE), behavioral intention to distance learning (BI)

7. Discussion

(1) H1: Perceived usefulness will have a positive effect on behavioral intention to distance learning.

Result: Supported (*t* statistic = 4.913, *P* value = 0.000)

Explanation: The analysis indicates a significant positive relationship between perceived usefulness (PU) and behavioral intention (BI) to engage in distance learning. This result supports the notion that when individuals perceive a technology as useful for their learning needs, they are more likely to express the intention to use it.

(2) H2: Perceived ease of use will have a positive effect on behavioral intention to distance learning.

Result: Supported (*t* statistic = 2.544, *P* value = 0.005)

Explanation: The statistical analysis reveals a significant positive impact of perceived ease of use (PEU) on behavioral intention (BI) to participate in distance learning. This suggests that when individuals find a system

easy to use, it positively influences their intention to adopt distance learning.

(3) H3: Facilitating conditions will have a positive effect on behavioral intention to distance learning.

Result: Supported (t statistic = 5.140, P value = 0.000)

Explanation: The findings strongly support the hypothesis that facilitating conditions (FC) positively influence behavioral intention (BI) in the context of distance learning. When individuals perceive that the necessary conditions for distance learning are in place, their intention to engage in it increases.

(4) H4: Computer self-efficacy will have a positive effect on behavioral intention to distance learning.

Result: Supported (t statistic = 1.948, P value = 0.026)

Explanation: The analysis indicates a statistically significant positive relationship between computer self-efficacy (CSE) and behavioral intention (BI) to participate in distance learning. This suggests that individuals with higher computer self-efficacy are more likely to express the intention to adopt distance learning.

(5) H5: Instructor efficiency will have a positive effect on behavioral intention to distance learning.

Result: Supported (t statistic = 4.550, P value = 0.000)

Explanation: The results support the hypothesis that instructor efficiency (IE) positively influences behavioral intention (BI) to participate in distance learning. This implies that when individuals perceive instructors as efficient in delivering content, their intention to engage in distance learning is positively impacted.

8. Conclusion and implications

The research concludes that several key factors significantly influence behavioral intention to engage in distance learning.

Perceived usefulness (H1): The study confirms a strong positive relationship between perceived usefulness and the intention to engage in distance learning. This aligns with the Technology Acceptance Model (TAM), indicating that when learners find technology useful for their needs, they are more inclined to use it.

Perceived ease of use (H2): The findings support the positive impact of perceived ease of use on the intention to participate in distance learning. Consistent with TAM, the easier the technology is perceived to be used, the greater the likelihood of its adoption by learners.

Facilitating conditions (H3): The study confirms that when learners believe that the essential conditions and assistance for distant learning are there, their inclination to participate in it is enhanced. This emphasizes the significance of external variables and resources in the implementation of educational technologies.

Computer self-efficacy (H4): There is a strong and positive relationship between an individual's belief in their ability to use computers effectively and their intention to engage in distance learning. Individuals with a high level of confidence in their computer skills are more inclined to embrace distance learning, underscoring the significance of self-efficacy in the acceptance of technology.

Instructor efficiency (H5): The research suggests that instructors who are both effective and efficient have a beneficial impact on learners' aspirations to participate in remote learning. The level of instruction has a crucial role in determining students' willingness to embrace and utilize online educational systems.

In summary, the study supports the fundamental principles of the Technology Acceptance Model and similar frameworks. It highlights that learners' intentions toward distance learning are influenced by factors such as perceived usefulness, perceived ease of use, facilitating conditions, computer self-efficacy, and instructor efficiency. These findings enhance our comprehension of the elements that impact the successful implementation of distance learning technologies.

This study enhances the Theoretical Framework of Distance Education. This research presents an

innovative theoretical framework for the field of distance education, utilizing the Technology Acceptance Model (TAM) and Transaction Distance Theory.

The study offers theoretical backing for educational policies and procedures. The research findings provide substantial theoretical support and practical guidance for educational decision-makers and practitioners. Research has shown that it can improve educational institutions' understanding of students' acceptance and needs for remote learning, hence facilitating the creation of more effective educational policies and teaching methods.

Disclosure statement

The authors declare no conflict of interest.

References

- [1] Paul R, Tait A, 2019, Special Issue: Open Universities: Past, Present and Future. *International Review of Research in Open and Distributed Learning*, 20(4): i–viii.
- [2] García-Peñalvo FJ, Corell A, Rivero-Ortega R, et al., 2021, Impact of the COVID-19 on Higher Education: An Experience-Based Approach, in *Information Technology Trends for a Global and Interdisciplinary Research Community*, IGI Global, Hershey, Pennsylvania, 1–18.
- [3] Ananga P, 2020, Pedagogical Considerations of E-Learning in Education for Development in the Face of COVID-19. *International Journal of Technology in Education and Science (IJTES)*, 4(4): 310–321.
- [4] Zuo M, Ma Y, Hu Y, et al., 2021, K-12 Students' Online Learning Experiences During COVID-19: Lessons from China. *Frontiers of Education in China*, 16(1): 1–30.
- [5] Milheim K, Fraenza C, Palermo-Kielb K, 2021, Supporting Student Initiated Mobile Device Use in Online Learning. *Online Learning*, 25(3): 267–288.
- [6] Kant N, Prasad KD, Anjali K, 2021, Selecting an Appropriate Learning Management System in Open and Distance Learning: A Strategic Approach. *Asian Association of Open Universities Journal*, 16(1): 79–97.
- [7] Hair JF, Hult GTM, Ringle C, et al., 2017, *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*, Sage Publications, Thousand Oaks, CA.
- [8] Henseler J, Ringle CM, 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.

Publisher's note

Bio-Byword Scientific Publishing remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.