UNDERSTANDING ONLINE LEARNING SATISFACTION AND CONTINUANCE INTENTION AMONG POSTGRADUATE MATERIALS SCIENCE STUDENTS AT PUBLIC UNIVERSITIES IN CHENGDU

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Abstract

This study investigated the impact of key factors on satisfaction and continuance intention toward online courses among postgraduate students in Materials Science at three public universities in Chengdu, China. A structured questionnaire was distributed, yielding 481 valid responses. Data were analyzed using Confirmatory Factor Analysis (CFA) to validate the measurement model, followed by Structural Equation Modeling (SEM) to test the hypothesized relationships. Results confirmed that all independent variables significantly influenced satisfaction, which in turn strongly predicted continuance intention. These findings support the robustness of the proposed model and offer actionable insights for improving online course design. The study concludes that enhancing learner satisfaction is essential for sustaining postgraduate engagement in digital learning environments and advancing institutional competitiveness in higher education.

Keywords: Online Courses, Course Satisfaction, Continuance Intention, Postgraduate Students

Introduction

The COVID-19 pandemic accelerated the shift to digital education, reshaping instructional delivery across higher education (Bao, 2020; Hodges et al., 2020). While online learning has enabled educational continuity, it also presents challenges for postgraduate students, particularly in STEM fields, where hands-on experiences and collaborative research are crucial for mastering complex concepts (Ali, 2020; Johnson et al., 2021). These challenges are even more pronounced in materials science, where practical experimentation and real-time data analysis are integral to learning. Understanding how students adapt to these limitations in digital settings is vital for improving learning outcomes.

Postgraduate students play a key role in driving innovation and require online learning environments that align with their research needs (Chen & Wang, 2022). Chengdu, a leading academic hub in western China, is well-positioned for studying postgraduate digital education due to its emphasis on technology and innovation (Zhang et al., 2023). The choice of materials science is strategic, as it aligns with China's national goals for technological advancement and sustainable development (Ministry of Education, 2022). Graduates in this field are expected to contribute to high-tech manufacturing and green technologies, making their learning experiences particularly relevant.

Although online learning has grown, research focusing specifically on factors influencing postgraduate students' satisfaction and continuance intention in materials science remains limited. This study addresses this gap by exploring key determinants using the Expectation-Confirmation Model (Bhattacherjee, 2001) and Technology Acceptance Model (Davis, 1989). It also examines how the technical nature of materials science influences online learning experiences, extending current knowledge in STEM education.

By centering on a specialized academic context, this research provides practical insights into designing more effective and sustainable online learning systems. It also emphasizes the importance of regional analysis to develop targeted strategies for enhancing student satisfaction and retention in Chinese public universities.

Literature Review

1. System Quality

System quality (SYQ) is a multidimensional construct encompassing technical features such as precision, reliability, accessibility, user-friendliness, and efficiency (DeLone & McLean, 2003; Tseng & Lee, 2018). In online learning, dimensions like system responsiveness and interface usability are crucial to fostering effective user-system interaction and enhancing satisfaction (Tam & Oliveira, 2016). Studies show that robust, stable system performance

contributes directly to user satisfaction by reducing frustration and increasing engagement (Alkhawaja et al., 2022). Based on these insights, this study proposes the following hypothesis:

H1: System quality significantly influences satisfaction with online learning.

2. Self-efficacy

Self-efficacy (SE), derived from Bandura's (1991) social cognitive theory, refers to an individual's belief in his or her own ability to perform actions necessary to achieve specific goals. In online learning, SE reflects users' confidence in navigating digital platforms and managing technology-based tasks (Liaw, 2008). Research indicates that learners with higher SE tend to engage more effectively, find platforms more useful, and experience greater satisfaction (Fianu et al., 2018; Shen et al., 2013). During COVID-19, a study at Xihua University found that 65% of Chinese students reported low self-efficacy in managing online learning, particularly in time management. Rural students showed even lower confidence levels, reflecting disparities in digital access (Zhou & Li, 2024). Drawing on prior literature, the following hypothesis is proposed:

H2: Self-efficacy significantly influences satisfaction with online learning.

3. Perceived Usefulness

Perceived usefulness (PU) is a key component of the Technology Acceptance Model, defined as the extent to which a user believes a system enhances performance (Davis, 1989). PU has been consistently shown to significantly influence user satisfaction across various domains, including social media (Liu et al., 2024), healthcare (Logsdon et al., 2024), and educational platforms (Hafifah & Sulistyo, 2023). These studies confirm that when users perceive digital platforms as beneficial to their learning or task efficiency, their satisfaction levels increase. This positive relationship underscores the importance of optimizing platform utility to enhance user satisfaction. Therefore, the following hypothesis is proposed:

H3: Perceived usefulness significantly influences satisfaction with online learning.

4. Perceived Ease of Use

Perceived ease of use (PEOU) refers to how effortless users find a system to operate (Davis, 1989). In online education, PEOU is a well-established predictor of both adoption and continued use of learning platforms (Venkatesh et al., 2003). Systems with intuitive interfaces promote user confidence and reduce learning barriers, especially for those with limited technological skills (Alalwan et al., 2017). Moreover, PEOU directly influences user satisfaction by minimizing complexity and enhancing the overall learning experience (Teo, 2010). This relationship underscores the importance of user-friendly platforms in promoting positive learning outcomes. Based on these insights, the following hypothesis is proposed:

H4: Perceived ease of use significantly influences satisfaction with online learning.

5. Confirmation

Confirmation (CONF) is the cognitive comparison between initial expectations and actual system performance (Bhattacherjee, 2001), based on Expectation-Confirmation Theory (Oliver, 1980). Positive confirmation reinforces both PU and satisfaction. In online learning, studies have found that confirmation enhances learners' motivation and engagement (Sørebø et al., 2009) and contributes directly to satisfaction when systems exceed expectations (Tan & Kim, 2015). Therefore, the following hypothesis is proposed:

H5: Confirmation significantly influences satisfaction with online learning.

6. Satisfaction

Satisfaction (SAT) is an affective-cognitive judgment that arises when users evaluate whether system performance meets expectations. In digital learning environments, satisfaction is shaped by instructional design, system quality, and user interaction (Cheng, 2020). Satisfied learners are more likely to remain engaged, demonstrate loyalty, and promote continued use (Bhattacherjee, 2001; Roca et al., 2006). A study of students in Hubei Province during COVID-19 found that online learning satisfaction was generally lower than traditional learning, influenced by class size, online teaching proportion, and network quality (Liu et al., 2023). Based on this understanding, the following hypothesis is proposed:

H6: Satisfaction significantly influences continuance intention with online learning.

7. Continuance Intention

Continuance intention (CI) reflects users' commitment to continue using an information system after initial adoption (Bhattacherjee, 2001). In e-learning, CI represents students' ongoing willingness to engage with online platforms beyond initial use, reflecting sustained learning engagement rather than just short-term usage (Chen et al., 2018; Zhou, 2013). Satisfied students are more likely to continue using the platform for future courses, highlighting the importance of positive learning experiences in fostering long-term engagement. Additionally, cognitive factors (e.g., value perception) and institutional support also influence CI, indicating its multidimensional nature (Lin & Wang, 2012; Venkatesh et al., 2003).

Research Framework

This study's conceptual framework is based on the Unified Theory of Acceptance and Use of Technology (UTAUT) and the Information Systems Success Model (ISSM). It integrates three prior models. The first, developed by Cheng (2019), explores the relationship between system quality and satisfaction. The second, proposed by Singh and Sharma (2021), analyzes the interconnections among self-efficacy, perceived usefulness, perceived ease of use, and

satisfaction. The third model, introduced by Cheng (2020), highlights the relationships among confirmation, satisfaction, and continuance intention. These theoretical foundations collectively inform the structure of the framework, as illustrated in Figure 1.

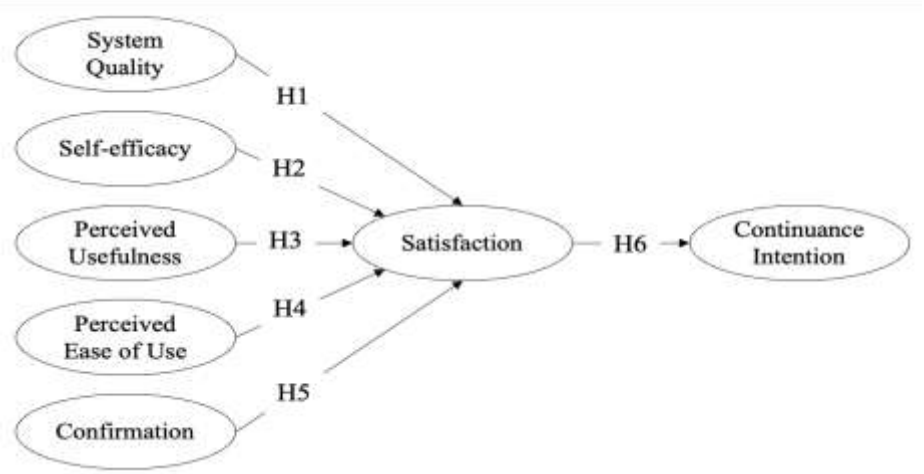


Figure 1 Conceptual Framework

Research Methodology

This study employed a quantitative, cross-sectional survey design to examine factors influencing postgraduate students' satisfaction and continuance intention in online learning. A structured questionnaire, adapted from validated scales in prior studies, was used to collect data. The instrument was translated into Chinese and back-translated for accuracy. Content validity was assessed by three Ph.D.-qualified experts (associate professors) using the Item-Objective Congruence (IOC) method, with all items scoring above 0.67. A pilot test with 30 students confirmed internal consistency, with Cronbach's alpha values exceeding 0.7.

The target population consisted of postgraduate students majoring in Materials Science and Engineering from three public universities in Chengdu: Sichuan University (SCU), Southwest Jiaotong University (SWJTU), and the University of Electronic Science and Technology of China (UESTC). A multi-stage non-probability sampling strategy was employed. Judgmental sampling identified students with relevant digital learning experience, quota sampling ensured proportional representation across academic years and institutions, and convenience sampling facilitated survey distribution. A total of 1,156 students were screened, and 500 questionnaires were distributed online, resulting in 481 valid responses.

Data analysis involved Confirmatory Factor Analysis (CFA) to assess construct validity, followed by Structural Equation Modeling (SEM) to test the hypothesized relationships. Statistical assumptions, normality and multicollinearity were verified before analysis. Skewness

and kurtosis metrics confirmed normality and VIF values indicated no multicollinearity issues. Missing data (less than 2%) were handled through mean imputation.

Ethical approval was obtained from the Institutional Review Boards (IRB) of the three universities. Informed consent was collected electronically, ensuring confidentiality and data privacy throughout the study.

1. Target Population and Sample Size

The target population comprised postgraduate students majoring in Materials Science and Engineering from three public universities in Chengdu: Sichuan University (SCU), Southwest Jiaotong University (SWJTU), and the University of Electronic Science and Technology of China (UESTC). Eligible participants were identified based on their academic background and a minimum of six months of experience with digital learning platforms.

A multi-stage non-probability sampling strategy was employed, combining judgmental, quota, and convenience sampling. Judgmental sampling was used to select students with relevant online learning experience, followed by quota sampling to ensure proportional representation across academic years and institutions. Finally, convenience sampling facilitated efficient distribution of the surveys. A total of 1,156 students were initially screened, with 500 questionnaires distributed online, yielding 481 valid responses (96.2% response rate). Follow-up reminders were sent to maximize participation. The minimum sample size requirement of 425 was determined based on the complexity of the structural model, following recommendations by Hair et al. (2019). The achieved sample size of 481 was sufficient for robust data analysis.

Table 1: Sample Units and Sample Size

Universities	Grade	Population Size	Proportional Sample Size
SCU	First-year students	120	52
	Second-year students	107	46
	Third-year students	126	55
SWJTU	First-year students	104	45
	Second-year students	109	47
	Third-year students	200	87
UESTC	First-year students	165	71
	Second-year students	106	46
	Third-year students	119	51
Total		**1,156**	**500**

Results and Discussion

1. Demographic Information

Among the 481 valid respondents, 30.3% (n = 146) were from Sichuan University, 35.8% (n=172) from Southwest Jiaotong University, and 33.9% (n=163) from the University of Electronic Science and Technology of China. Male students comprised 60.3% (n=290) of the sample, while female students accounted for 39.7% (n=191). In terms of academic level, 33.7% (n=162) were first-year, 27.8% (n=134) second-year, and 38.5% (n=185) third-year postgraduate students. Overall, the sample reflects balanced representation across institutions and academic years, with majority of male respondents, typical of engineering-related disciplines.

2. Confirmatory Factor Analysis (CFA)

Confirmatory Factor Analysis (CFA) was conducted as the initial step in validating the measurement model within the Structural Equation Modeling (SEM) framework. All standardized factor loadings were statistically significant and exceeded the recommended threshold of 0.50, indicating adequate indicator reliability (Hair et al., 2019). Composite Reliability (CR) values for all constructs surpassed the 0.70 benchmark, demonstrating satisfactory internal consistency (Fornell & Larcker, 1981). Average Variance Extracted (AVE) values also met or approached the minimum recommended threshold of 0.50, supporting convergent validity.

Table 2: Confirmatory Factor Analysis Results

Variable	Source of Questionnaire (Measurement Indicator)	No. of Item	Cronbach's Alpha	Factor Loading	CR	AVE
SYQ	Cheng (2019)	4	0.851	0.720-0.796	0.851	0.589
SE	Singh and Sharma (2021)	5	0.821	0.713-0.750	0.821	0.535
PU	Singh and Sharma (2021)	5	0.831	0.735-0.752	0.831	0.552
PEOU	Singh and Sharma (2021)	4	0.826	0.717-0.755	0.826	0.543
CONF	Cheng (2020)	3	0.860	0.750-0.752	0.863	0.678
SAT	Cheng (2019)	4	0.835	0.705-0.791	0.835	0.560
CI	Cheng (2020)	4	0.807	0.693-0.767	0.808	0.513

Note: Composite Reliability (CR) and Average Variance Extracted (AVE) are acceptable at value greater than 0.7 and 0.5, respectively.

The overall measurement model fit was assessed using a combination of absolute and incremental fit indices. Goodness-of-fit metrics presented in Table 3, all met their respective recommended cut-off values, indicating an acceptable model fit.

Table 3: Goodness of Fit for Measurement Model

Fit Index	Recommended Value and Source	Statistical Value
CMIN/df	<5.00 (Al-Mamary & Shamsuddin, 2015)	1.212
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.946
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.933
NFI	≥ 0.80 (Wu & Wang, 2006)	0.932
CFI	≥ 0.80 (Bentler, 1990)	0.987
TLI	≥ 0.80 (Sharma et al., 2005)	0.985
RMSEA	< 0.08 (Pedroso et al., 2016)	0.021

Note: CMIN/df = The ratio of the chi-square value to degree of freedom, GFI = goodness-of-fit index, AGFI = adjusted goodness-of-fit index, TLI = Tucker Lewis index, NFI = normalized fit index, CFI = comparative fit index, RMSEA = root mean square error of approximation

Discriminant validity was assessed using the Fornell-Larcker criterion, which compares the square root of each construct's AVE to its correlations with other constructs. As shown in Table 4, all constructs met the threshold, indicating adequate discriminant validity within the measurement model.

Table 4: Discriminant Validity Output

Variable	SYQ	SE	PU	PEOU	CONF	SAT	CI
SYQ	**0.767**						
SE	0.316	**0.731**					
PU	0.075	0.056	**0.743**				
PEOU	0.121	0.112	0.075	**0.737**			
CONF	0.077	0.025	0.040	0.050	**0.823**		
SAT	0.259	0.206	0.200	0.261	0.120	**0.748**	
CI	0.222	0.228	0.204	0.205	0.051	0.328	**0.716**

Note: The diagonally listed value is the AVE square roots of the variables

3. Structural Equation Model (SEM)

After validating the measurement model through Confirmatory Factor Analysis, the structural model was estimated using Structural Equation Modeling (SEM) to examine the causal relationships among the latent constructs. Structural model fit was assessed using a

combination of absolute and incremental fit indices. In accordance with the, all key indicators in Table 5 met the recommended thresholds, indicating an overall model fit. These results confirmed that the hypothesized structural relationships were well supported by the data.

Table 5: Goodness of Fit for Structural Equation Model (SEM)

Fit Index	Recommended Value and Source	Statistical Value
CMIN/df	<5.00 (Al-Mamary & Shamsuddin, 2015)	1.467
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.932
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.919
NFI	≥ 0.80 (Wu & Wang, 2006)	0.913
CFI	≥ 0.80 (Bentler, 1990)	0.971
TLI	≥ 0.80 (Sharma et al., 2005)	0.967
RMSEA	< 0.08 (Pedroso et al., 2016)	0.031

Note: CMIN/df = The ratio of the chi-square value to degree of freedom, GFI = goodness-of-fit index, AGFI = adjusted goodness-of-fit index, TLI = Tucker Lewis index, NFI = normalized fit index, CFI = comparative fit index, RMSEA = root mean square error of approximation

4. Research Hypothesis Testing Result

The hypothesis testing results, summarized in Table 6, indicate that all proposed hypotheses were supported. Satisfaction was found to be the most significant predictor of continuance intention, while perceived ease of use emerged as the strongest predictor of satisfaction. All five independent variables exhibited significant positive effects on satisfaction, which in turn significantly influenced continuance intention among postgraduate students.

Table 6: Hypothesis Testing Result

Hypothesis	Standardized Estimate (β)	t-Value	Result
H1: SYQ ⟶ SAT	0.217	4.197*	Supported
H2: SE ⟶ SAT	0.152	2.930*	Supported
H3: PU ⟶ SAT	0.212	4.050*	Supported
H4: PEOU ⟶ SAT	0.277	5.144*	Supported
H5: CONF ⟶ SAT	0.114	2.272*	Supported
H6: SAT ⟶ CI	0.421	7.138*	Supported

Note: *= $p < 0.05$

H1: System quality had a significant positive impact on satisfaction (β=0.217, t=4.197). This supports the Information Systems Success Model (DeLone & McLean, 2003) and aligns with Tam and Oliveira (2016), suggesting that features such as system responsiveness, reliability, and ease of access enhance user satisfaction in digital learning environments.

H2: Self-efficacy significantly influenced satisfaction (β=0.152, t=2.930). This finding aligns with Bandura's (1997) Social Cognitive Theory and supports Liaw (2008) and Fianu et al. (2018), indicating that postgraduate students with higher confidence in using technology are more likely to experience satisfaction in online learning environments.

H3: Perceived usefulness was confirmed as a significant predictor of satisfaction (β=0.212, t=4.050). This supports the Technology Acceptance Model (Davis, 1989) and related research by Venkatesh et al. (2003) and Hafifah and Sulistyo (2023), demonstrating that students who perceive online learning as enhancing their performance report higher satisfaction.

H4: Perceived ease of use was the most influential factor on satisfaction (β=0.277, t=5.144). This result aligns with the TAM model and findings by Islam et al. (2018) and Alalwan et al. (2017), who emphasized that user-friendly systems substantially increase learning satisfaction, especially among postgraduate students.

H5: Confirmation also showed a significant effect on satisfaction (β=0.114, t=2.272), validating the Expectation-Confirmation Model (Bhattacherjee, 2001). This supports findings from Roca et al. (2006) and Tan and Kim (2015), indicating that when online systems meet students' expectations, satisfaction improves, especially in long-term usage scenarios.

H6: Satisfaction was found to be the most significant predictor of continuance intention (β=0.421, t=7.138), reaffirming its central role in post-adoption behavior as proposed by Bhattacherjee (2001). This result is consistent with Cheng (2020) and Liu et al. (2023), who highlight that satisfaction significantly enhances students' willingness to continue using online platforms.

Conclusions, Recommendations, Limitations and Future Research

1. Conclusions

This study explored the factors influencing postgraduate students' satisfaction and continuance intention in online learning within Materials Science and Engineering programs at three public universities in Chengdu, China. Drawing on the Technology Acceptance Model (TAM), Expectation-Confirmation Model (ECM), and Information Systems Success Model (ISSM), the findings validated a conceptual framework through survey data and structural modeling techniques.

Satisfaction emerged as the strongest predictor of continuance intention, reinforcing the importance of positive user experiences for sustained engagement. Perceived ease of use had the highest impact on satisfaction, supporting TAM's assertion that intuitive design enhances acceptance. System quality also significantly influenced satisfaction, highlighting the need for reliable and accessible digital platforms in online learning.

Compared to general undergraduate studies (Alalwan et al., 2017; Islam et al., 2018), this study emphasizes the unique demands of postgraduate STEM students, such as the need for platform reliability and hands-on simulation capabilities. These findings suggest that robust, discipline-specific tools and seamless system functionality are crucial for enhancing learning experiences in technical fields.

The study underscores the need for user-friendly and academically relevant online platforms that support postgraduate learning. Addressing both technical quality and user experience can enhance satisfaction and promote long-term engagement in digital learning environments, aligning with China's digital transformation goals in higher education.

2. Recommendations

To enhance the effectiveness and sustainability of online learning for postgraduate students in Materials Science and Engineering, three strategic priorities are proposed. First, universities should strengthen system infrastructure and usability by upgrading digital platforms, integrating discipline-specific research tools, and offering responsive technical support. Simplified workflows, intuitive interfaces, and emerging technologies such as AR-based assistance can further improve accessibility and user experience.

Second, institutions should focus on building student capability and engagement through structured training programs that develop digital and research competencies at multiple levels. Peer mentoring and collaborative initiatives can enhance self-efficacy and promote ongoing learner development.

Third, reinforcing the academic relevance of online learning is essential. Embedding applied research tasks, modeling real-world tool usage in teaching, and incorporating motivational strategies, such as achievement recognition and research-based rewards, can help sustain satisfaction and drive long-term use. Together, these actions can support a more robust, engaging, and meaningful digital learning environment for postgraduate STEM education.

3. Limitations and Future Research

This study focused on materials science postgraduates from three Chengdu universities, which may limit generalizability to other disciplines or regions. Its cross-sectional design restricts causal interpretations, and reliance on self-reported data introduces potential bias.

Future research should expand to other STEM disciplines and regions to enhance representativeness. Longitudinal studies are recommended to track changes in satisfaction and continuance intention over time. Exploring technologies such as AI, VR, and AR could also deepen engagement through immersive learning experiences. Cross-cultural comparisons and behavioral analytics, such as platform usage and interaction data, would further validate the findings and reveal regional differences in digital learning adoption. These extensions would provide richer insights into online learning in specialized academic fields and support the development of more effective digital education strategies.

Reference

Alalwan, A. A., Dwivedi, Y. K., & Rana, N. P. (2017). Factors influencing adoption of mobile banking by Jordanian bank customers: Extending UTAUT2 with trust. *International Journal of Information Management, 37*(3), 99–110. https://doi.org/10.1016/j.ijinfomgt.2017.01.002

Ali, W. (2020). Online and remote learning in higher education institutes: A necessity in light of COVID-19 pandemic. *Higher Education Studies, 10*(3), 16–25. https://doi.org/10.5539/hes.v10n3p16

Alkhawaja, M. I., Abd Halim, M. S., Abumandil, M. S. S., & Al-Adwan, A. S. (2022). System quality and student's acceptance of the e-learning system: The serial mediation of perceived usefulness and intention to use. *Contemporary Educational Technology, 14*(2), Article ep350. https://doi.org/10.30935/cedtech/11525

Al-Mamary, Y. H., & Shamsuddin, A. (2015). Testing of the technology acceptance model in context of Yemen. *Mediterranean Journal of Social Sciences, 6*(4), 88–96.

Bandura, A. (1991). Social cognitive theory of self-regulation. *Organizational Behavior and Human Decision Processes, 50*(2), 248–287. https://doi.org/10.1016/0749-5978(91)90022-L

Bandura, A. (1997). Self-efficacy: *The exercise of control*. W. H. Freeman.

Bao, W. (2020). COVID-19 and online teaching in higher education: A case study of Peking University. *Human Behavior and Emerging Technologies, 2*(2), 113–115. https://doi.org/10.1002/hbe2.191

Bentler, P. M. (1990). Comparative fit indexes in structural models. *Psychological Bulletin, 107*(2), 238–246.

Bhattacherjee, A. (2001). Understanding information systems continuance: An expectation-confirmation model. *MIS Quarterly, 25*(3), 351–370. https://doi.org/10.2307/3250921

Chen, Y., Chen, N.-S., & Tsai, C.-C. (2018). Investigating MOOC continuance intention: The role of intrinsic motivation. *Computers in Human Behavior, 85*, 30–39. https://doi.org/10.1016/j.chb.2018.03.028

Chen, Y., & Wang, Y. (2022). Digital competence and online learning satisfaction: Evidence from Chinese postgraduate students. *Computers & Education, 185*, Article 104516. https://doi.org/10.1016/j.compedu.2022.104516

Cheng, Y.-M. (2019). A hybrid model for exploring the antecedents of cloud ERP continuance: Roles of quality determinants and task-technology fit. *International Journal of Web Information Systems, 15*(2), 215–235. https://doi.org/10.1108/IJWIS-07-2018-0056

Cheng, Y.-M. (2020). Continuance intention to use MOOCs: Integrating the technology acceptance model and expectation confirmation theory. *British Journal of Educational Technology, 51*(1), 330–356. https://doi.org/10.1111/bjet.12839

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

DeLone, W. H., & McLean, E. R. (2003). The DeLone and McLean model of information systems success: A ten-year update. *Journal of Management Information Systems, 19*(4), 9–30. https://doi.org/10.1080/07421222.2003.11045748

Fianu, E., Blewett, C., Ampong, G. O. A., & Ofori, K. S. (2018). Factors affecting MOOC usage by students in selected Ghanaian universities. *Education and Information Technologies, 23*(2), 815–834. https://doi.org/10.1007/s10639-017-9635-9

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39–50. https://doi.org/10.1177/002224378101800104

Hafifah, G. N., & Sulistyo, G. H. (2023). Teachers' ICT literacy and ICT integration in ELT in the Indonesian higher education setting. *Turkish Online Journal of Distance Education, 21*(3), 186–198. https://doi.org/10.17718/tojde.983077

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate data analysis* (8th ed.). Cengage Learning.

Hodges, C., Moore, S., Lockee, B., Trust, T., & Bond, A. (2020). The difference between emergency remote teaching and online learning. *Educause Review, 27*, 1–12. https://er.educause.edu/articles/2020/3/the-difference-between-emergency-remote-teaching-and-online-learning

Islam, A. K. M. N., Mäntymäki, M., & Bhattacherjee, A. (2018). E-learning system use and its outcomes: Moderating role of perceived compatibility. *Telematics and Informatics, 35*(1), 342–354. https://doi.org/10.1016/j.tele.2017.12.015

Johnson, N., Veletsianos, G., & Seaman, J. (2021). US faculty and administrators' experiences and approaches in the early weeks of the COVID-19 pandemic. *Online Learning, 25*(1), 6–21. https://doi.org/10.24059/olj.v25i1.2462

Liaw, S.-S. (2008). Investigating students' perceived satisfaction, behavioral intention, and effectiveness of e-learning: A case study of the Blackboard system. *Computers & Education, 51*(2), 864–873. https://doi.org/10.1016/j.compedu.2007.09.005

Lin, W.-S., & Wang, C.-H. (2012). Antecedents to continued intentions of adopting e-learning system in blended learning instruction: A contingency framework based on models of information system success and task-technology fit. *Computers & Education, 58*(1), 88–99. https://doi.org/10.1016/j.compedu.2011.07.008

Liu, T., De Costa, F., & Yasing, M. A. I. (2024). Perceived usefulness as a mediating variable on the relationship between video quality and audience emotional engagement in social media. *Studies in Media and Communication, 13*(1), 125–135. https://doi.org/10.11114/smc.v13i1.7234

Liu, X., Zhang, Y., & Wang, R. (2023). Impact of online learning during the COVID-19 pandemic on student satisfaction: Evidence from Hubei Province, China. *Frontiers in Education, 8*, 1097910. https://doi.org/10.3389/feduc.2023.1097910

Logsdon, M. C., Kondaurova, I., Zhang, N., Das, S., Edwards, B. D., Mitchell, H., & Popa, D. O. (2024). Perceived usefulness of robotic technology for patient fall prevention. *Workplace Health & Safety, 72*(12), 542–549. https://doi.org/10.1177/21650799231188634

Ministry of Education. (2022). *China's education modernization 2035 plan: Strategic priorities and developmental goals*. Ministry of Education, People's Republic of China. Retrieved from http://en.moe.gov.cn/documents/reports/2022

Oliver, R. L. (1980). A cognitive model of the antecedents and consequences of satisfaction decisions. *Journal of Marketing Research, 17*(4), 460–469. https://doi.org/10.1177/002224378001700405

Pedroso, R., Zanetello, L., Guimarães, L., Pettenon, M., Gonçalves, V., Scherer, J., Kessler, F., & Pechansky, F. (2016). Confirmatory factor analysis (CFA) of the crack use relapse scale (CURS). *Archives of Clinical Psychiatry, 43*(3), 37–40. https://doi.org/10.1590/0101-60830000000088

Roca, J. C., Chiu, C.-M., & Martínez, F. J. (2006). Understanding e-learning continuance intention: An extension of the Technology Acceptance Model. *International Journal of Human-Computer Studies, 64*(8), 683–696. https://doi.org/10.1016/j.ijhcs.2006.01.003

Sharma, G. P., Verma, R. C., & Pathare, P. (2005). Mathematical modeling of infrared radiation thin layer drying of onion slices. *Journal of Food Engineering, 71*(3), 282–286. https://doi.org/10.1016/j.jfoodeng.2004.11.036

Shen, D., Cho, M.-H., Tsai, C.-L., & Marra, R. (2013). Unpacking online learning experiences: Online learning self-efficacy and learning satisfaction. *Internet and Higher Education, 19*, 10–17. https://doi.org/10.1016/j.iheduc.2013.04.001

Sica, C., & Ghisi, M. (2007). The Italian versions of the Beck Anxiety Inventory and the Beck Depression Inventory-II: Psychometric properties and discriminant power. In M. A. Lange (Ed.), *Leading-edge psychological tests and testing research* (pp. 27–50). Nova Science Publishers.

Singh, N., & Sharma, S. K. (2021). Examining the role of psychological factors in influencing smartphone addiction: A mediation model of loneliness and depression. *Asian Journal of Psychiatry, 54*, 102247. https://doi.org/10.1016/j.ajp.2020.102247

Sørebø, Ø., Halvari, H., Gulli, V. F., & Kristiansen, R. (2009). The role of self-determination theory in explaining teachers' motivation to continue to use e-learning technology. *Computers & Education, 53*(4), 1177–1187. https://doi.org/10.1016/j.compedu.2009.06.001

Tam, C., & Oliveira, T. (2016). Understanding the impact of m-banking on individual performance: DeLone & McLean and TTF perspective. *Computers in Human Behavior, 61*, 233–244. https://doi.org/10.1016/j.chb.2016.03.016

Tan, G. W. H., & Kim, S. S. (2015). The moderating role of trust in cloud computing adoption: A meta-analysis. *Information & Management, 52*(8), 1003–1017. https://doi.org/10.1016/j.im.2015.07.006

Teo, T. (2010). A path analysis of pre-service teachers' attitudes to computer use: Applying and extending the Technology Acceptance Model in an educational context. *Interactive Learning Environments, 18*(1), 65–79. https://doi.org/10.1080/10494820802231327

Tseng, M.-L., & Lee, C.-W. (2018). A comprehensive framework for the success of information systems: The case of e-commerce. *International Journal of Information Management, 38*(1), 112–122. https://doi.org/10.1016/j.ijinfomgt.2017.07.006

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

Wu, J. H., & Wang, Y. M. (2006). Measuring KMS success: A respecification of the DeLone and McLean's model. *Information & Management, 43*(6), 728–739. https://doi.org/10.1016/j.im.2006.05.002

Zhang, Y., Li, H., & Wang, X. (2023). Urban innovation ecosystems in western China: The case of Chengdu's higher education clusters. *Asia Pacific Education Review, 24*(1), 51–64. https://doi.org/10.1007/s12564-023-09796-7

Zhou, J., & Li, H. (2024). Self-efficacy in online learning environments during COVID-19: A study of Chinese university students. *BMC Medical Education, 24*, 5890. https://doi.org/10.1186/s12909-024-05890-5

Zhou, T. (2013). An empirical examination of continuance intention of mobile payment services. *Decision Support Systems, 54*(2), 1085–1091. https://doi.org/10.1016/j.dss.2012.10.034