



Factors affecting students' online courses learning behaviors

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Abstract

Online course learning is an important part of higher education curriculum. However, the factors influencing college students' online course learning behavior are poorly understood. The purpose of this study is to analyze the factors affecting college students' online course learning behavior. This study integrated the Information System Success Model, the Technology Acceptance Model, and Self-efficacy Theory to construct an online course learning acceptance model. A total of 308 college students participated from China filled out the questionnaire, and 18 of them also participated in a semi-structured interview. The structural equation model was used to analyze the research data. The empirical analysis showed that self-efficacy has a positive impact on perceived usefulness and perceived ease-of-use; Perceived usefulness, attitude, system quality, and information quality affect users' behavioral intentions positively; Perceived ease of use has a positive effect on users' attitudes and perceived usefulness; and perceived usefulness has a direct effect on users' attitudes; Furthermore, behavioral intention can predict the actual use of online courses by college students. In addition, we will discuss these results and provide recommendations. This study provides a theoretical basis for the study of online course learning acceptance and extends the technology acceptance model. The research can provide inspiration for the design of online course learning and the decision-making of management institutions, and contribute to the sustainable development of education.

Keywords Learned behavior · Influence factor · E-learning · Higher education · China

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1 Introduction

The outbreak of the COVID-19 compelled colleges to suspend traditional offline courses to reduce the spread of virus, which was eventually changed the model of teaching, namely the prevalence of online teaching (Park & Lee, 2021). Of course, this has been made possible by the development of information in the education sector. The advancement of communication technology has changed the way students learn today (Martin et al., 2011). Consequently, online learning is an important link in higher education (Paechter et al., 2010).

Online learning focuses on imparting knowledge to students through computer technology (Binyamin et al., 2019). In response to issues, such as the unprecedented school closures brought by the COVID-19 pandemic, governments around the world are promoting online as a substitute of learning outside of school (Ho et al., 2020). Many colleges around the world have implemented online learning (Almaiah et al., 2020; Kanetaki et al., 2021). China's national education regulations on "suspended classes, ongoing learning" (Zhang et al., 2020), released in March 2020, boosted the explosive development of online learning, including the development of communicates technology and conference apps, such as Tencent Meeting and DingTalk. Banihashem et al. (2023) believes that blended education that includes online learning is an important way of post-pandemic education. The benefits of online learning for education cannot simply be ignored (Fang et al., 2023). Online learning has many advantages. For example, students can participate in various learning activities in a virtual environment (Al-Rahmi et al., 2018; Salloum et al., 2019). They access a lot of knowledge and information at any time and engage in online discussions, which enhance the teacher-student relationship (Salloum et al., 2019). This new model of learning facilitates online learning and promotes knowledge repetition, sharing, and expansion (Alajmi & Sadiq, 2016). Although online learning brings many benefits to students, it is difficult to implement its advantages if students refuse to learn online (Nguyen et al., 2022).

Currently, scholars have conducted research on users' online learning intentions. For example, Banihashem et al. (2023) considers online learning as a part of blended education and explores the attitudes and views of teachers and students in the Netherlands towards blended education. Fathema et al. (2015) incorporated self-efficacy into a technology acceptance model (TAM) to explore teachers' use of learning management systems. Benchrifia et al. (2017) proposed that attitude has a significance on the preference of college students to learn online. According to Prasetyo et al. (2021), online learning is a feasible solution to transform face-to-face teaching into online learning, and it can facilitate students' learning. However, previous studies (Chayomchai, 2020; Khalid et al., 2021) focused on the learning effectiveness of students under the use of technology, yet research into students' application of online learning in developing countries is still limited (Jameel et al., 2020; Samsudeen & Mohamed, 2019).

Technology acceptance models are widely used as an important theory for user behavior research. Some studies (Ngai et al., 2007; Ong et al., 2004) applied the TAM to probe into students' intentions to use technology for learning. Although the technology acceptance model is an excellent user technology acceptance prediction model,

it does not contain some other significant belief factors (Benbasat & Barki, 2007), so it needs to be expanded to fit the context of online course learning. Therefore, this study will take TAM model as the theoretical basis and add a new dimension to further explain the acceptance of online course learning. Bandura (1977, 1989) defined self-efficacy (SE) as users' personal estimate or belief of their performance capacity in a situation or task. It is one of the guiding factors of human behavior (Bandura, 2006). Previous studies (Abdullah & Ward, 2016; Ibrahim et al., 2017) argued that individuals with a higher sense of SE perceive the ease of use and availability of technology more strongly. The Information System Success Model (ISSM) proposed by DeLone et al. (2003) suggests that system quality (SYSQ), information quality (IQ), and service quality (SERQ) influence users' behaviors in using technology. As online learning is a new model of teaching, the acceptance of students is affected by the course content and the relevant quality of the content provider, the teacher, and the transmission media, the learning system. It can be argued that future online education should fully understand the needs and characteristics of users (Dede, 1996; Murphy & Pinnegar, 2018). Therefore, in addition to the usefulness of online course learning, the users' abilities, as well as the IQ, system SYSQ, and SERQ of online courses should also be considered.

Under the impact of the COVID-19, both teachers and educational institutions, such as colleges, must pay attention to online course learning, including online teaching models and methods, student learning behaviors, and learning effectiveness. It is essential to study students' tendency for online learning from their perspective (Bali & Liu, 2018), as the effectiveness of online courses is affected by the actual use of the students (Chahal & Rani, 2022). The factors that affect student's use intentions of online courses and their mechanism of action should be explored (Brahmasrene et al., 2012). Therefore, our research aims to determine the influencing factors of college students' online course learning behavior. By integrating the TAM, the Self-efficacy Theory, and the Information System Success Model, this study aims to explore the effects of self-efficacy, information quality, system quality, service quality, perceived usefulness (PU), perceived ease-of-use (PEOU), and attitudes (ATT) on the behavioral intentions (BI) and actual use (AU) online courses by college students. This study also developed an acceptance model of online courses and conducted an empirical study on students from two colleges in China to predict the online course learning behaviors of college students.

2 Theoretical development and hypotheses

2.1 Technology acceptance model

The TAM proposed by Davis (1986) is an excellent theory of user behavior that can be used to forecast technology adoption by user. The model suggests that PU and PEOU are important factors affecting the intended and actual use of technologies users. It has been widely use for predicting users' technology adoption (Bagozzi, 2007). In recent years, the TAM has been extensively applied to mobile payments

(Rafidinal & Senalasari, 2021), online learning (Al-Azawei & Lundqvist, 2015), and online video (Nagy, 2018).

In the TAM, perceived usefulness means that individual think that use of the technology can enhance their performance (Herrenkind et al., 2019). Chang and Tung (2008) defined perceived usefulness as the extent to which users believe that using technology could increase their online learning performance. In the TAM, PU is related to attitudes and intentions, which are the main variables affecting users' behavioral intentions regarding technology (Moon & Kim, 2001). PU is directly affected by PEOU. When the user thinks a technology is simple, they tend consider the technology to be useful. Cheng (2011) suggested that PU of an online learning system directly and significantly affect user's attitudes. Chaveesuk and Chaiyasoonthorn (2022) investigated Thai students' preference to use cloud classrooms, and found that PU has a positive impact on users' BI. Based on the above, this research proposes hypotheses:

H1: Perceived usefulness has a positive impact on college students' behavioral intentions in online courses.

H2: Perceived usefulness has a positive impact on college students' attitudes toward online courses.

Davis (1985) defined perceived ease of use as the extent to which an individual believes that a technology system is easy to use. The value of PEOU in the TAM has been confirmed by some studies (Davis, 1989; Davis et al., 1992). According to the TAM, PEOU affects users' attitudes and usefulness, as well as users' attitudes toward online learning systems (Liu et al., 2009), and significantly affects PU of online learning systems (Liu et al., 2009). Liu et al. (2010) indicated that PEOU has a positive impact on the use of online learning communities. Previous studies (Park, 2009; Chang et al., 2012) demonstrated the direct and decisive effect of PEOU on ATT. Therefore, this study holds that PEOU directly affects PU and students' attitudes in online learning. Hence, the hypotheses are proposed:

H3: Perceived ease of use has a positive impact on college students' perceptions of the usefulness of online courses.

H4: Perceived ease of use has a positive impact on college students' attitudes toward online courses.

Attitude is defined as the degree of positive or negative feelings of users towards online learning (Hussein, 2017). It is an important determinant of technology usage by users (Davis, 1989), and has a direct positive impact on users' BI (Alharbi & Drew, 2014). It has been proven that users tend to have a positive attitude toward a technology if they find it useful and easy to use. Revyathi & Tselios. (2019) suggested that users' attitudes significantly affect their intentions to use technology. BI refer to the effort that users make in performing a behavior (Davis et al., 1989). The TAM suggests that users' behavior intentions affect their actual use of the technology (Davis et al., 1989). Previous studies (Abdullah & Toycan, 2018; Fathema et al.,

2015) confirmed the direct impact of users' BI on their actual use. Chahal and Rani (2022) studied the acceptance of online learning by college students in India, and confirmed the effect of users' behavioral intentions on their actual use. This study defined BI as the intention of college students in online courses (Liao & Lu, 2008). Hence, the hypotheses are proposed:

H5: Attitude of college students towards online courses directly affects their behavioral intentions.

H6: Behavioral intentions of college students positively affects their actual use of online courses.

2.2 Information system success model

Based on their information system (DeLone & McLean, 1992), DeLone et al. (2003) proposed an updated Information System Success Model, which includes the inter-related components of information system success (e.g., IQ, SYSQ, SERQ, BI, use, and user satisfaction). The model interprets information quality as the accuracy and completeness of information, SYSQ as the accuracy and speed of systems, and SERQ as the quality, speed, and completeness of services. In the model, the systems can be evaluated based on IQ, SYSQ, and SERQ, and these characteristics can significantly influence user intention or AU and user satisfaction.

The information content refers to the accuracy, timeliness, and relevance of the information presented (Yuan et al., 2020), and the clarity of information in the system will facilitate its use by users (Balkaya & Akkucuk, 2021). In the study of Rokhim et al. (2022) on the acceptance of learning management systems, IQ was found to directly affect users' behavioral intentions as an external variable. Zhang et al. (2022) studied the preference to pay for Python courses, while the quality of Python courses was considered as IQ. They discovered that course quality has a significant effect on users' ongoing use intention. The quality of content information of online courses is particularly important for users when deciding whether to continue online learning (Liu et al., 2010). Pham et al. (2022) pointed out that the competitive online learning market makes the quality of online courses even more critical. Therefore, it is necessary to consider the influence of IQ on students' learning behavior in online learning. Hence, the hypothesis is proposed as follows:

H7: Information quality significantly affects college students' behavioral intentions in online course learning.

The Information System Success Model (DeLone & McLean, 2003) defines service quality as the quality, speed, and completeness of service. Tj and Tanuraharjo (2020) suggested that the quality of online learning services includes SYSQ, teachers, and course materials, and covers multiple dimensions. Sugandini and Istanto (2022) held that users' choice of using online learning is affected by the SERQ. The significant impact of service quality on user intention has been confirmed in previous studies

(Akdim et al., 2022; Twum et al., 2022). Zhang et al. (2022) explored the learners' learning satisfaction and continued purchase intention of paid online Python courses in China, and found that SERQ and SYSQ have a direct positive impact on users' intentions. In summary, under the impact of the COVID-19 pandemic, colleges and other educational institutions, as providers of online courses, should improve the SERQ and SYSQ of these courses, so as to change their online course learning behaviors. Therefore, the hypotheses are proposed:

H8: Service quality has a direct positive impact on the behavioral intentions of college students in online courses.

H9: System quality has a direct and positive impact on the behavioral intentions of college students in online courses.

2.3 Self efficacy theory

Bandura's (1977) defined Self efficacy as users' estimate or belief of their performance capacity in a situation or task. It is one of the guiding factors of human behavior (Bandura, 2006). It is consisted of perceptual beliefs related to specific activities of users, thus, it applies to the measurement of a specific situation or task (Bandura, 2006). Under an online learning scenario, SE is defined as a student's level of confidence or capacity to learn using an online learning technology system (Cai et al., 2019). Users with a higher sense of SE are less worried about using the technology, and are more confident in performing technology-related tasks (Downey & Kher, 2015). The meta-analysis of Abdullah et al. (2016) on factors affecting the adoption of online learning noted that SE is a key external factor in the TAM model. The positive effect of SE on PEOU and PU was also confirmed in the review of Abdullah and Ward (2016) and Doan's (2021) study on Vietnamese users. Previous studies (Ong et al., 2004; Park, 2009) confirmed the positive effect of SE on PU and PEOU. Chaveesuk and Chaiyasoonthorn (2022) investigated Thai students' use of Cloud Classroom, and found that SE has a positive impact on PU and PEOU. The positive effect of the SE variable on PEOU and PU was also confirmed in Ibrahim et al. (2017). SE determines users' confidence in their capacity to perform technical behaviors, which is a judgment of their capacity required to achieve performance. This study incorporates SE to probe into the impact of college students' confidence in online course learning on their online course learning behaviors. This study defined SE in online courses as students' judgments on their capability or confidence in online learning technologies and online courses. This study suggests that confidence helps students to perceive more ease of use when taking online courses, and such beliefs facilitate better online course learning. They will be enthusiastic and confident about online course learning and will not find it difficult. Therefore, the hypothesis is proposed:

H10: Self efficacy has a direct positive effect on perceived usefulness.

H11: Self efficacy has a direct positive effect on perceived ease of use.

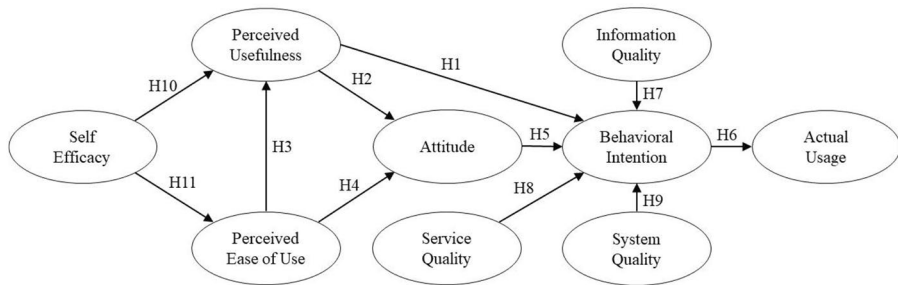


Fig. 1 Online Course Learning Acceptance Model

In summary, this study proposes an online course learning acceptance model as shown in Fig. 1, which contains nine constructs and 11 research hypotheses.

3 Methodology

A mixed method combining quantitative and qualitative approaches was used in this study. Data for the study were obtained from students at two universities in China. Quantitative data were obtained by completing paper questionnaires with the consent of the participants; subsequently, qualitative data were obtained by conducting semi-structured interviews in full compliance with the principles of voluntariness and initiative of the participants.

3.1 Participants

The subjects of this study were the students of a comprehensive university and a medical university in Guangdong Province, as they take up a higher percentage among colleges in China. The selected colleges are among the top in Guangdong Province in terms of annual enrollment and are representative of the provincial key institutions. The amount of data in this study follows the recommendation of Kline (2015) of 5–10 times the number of questions. A total of 308 valid questionnaires were received. Table 1 shows the specific demographic characteristics. As seen, there were 145 male participants (47.3%), and 163 female participants (52.9%). Among all participants, there were 247 undergraduates (80.2%), and postgraduates was only 61. The disparity between the proportion of undergraduates and postgraduates is because this study mainly targeted at college students, and the teaching objects of these two colleges are mainly undergraduates with a small proportion of enrollment for postgraduates. Among all participants, 27.9% majored in medicine, 19.8% in engineering, 18.9% in humanities and arts, 17.5% in science, and 15.9% in others. In the past year, 118 (38.3%) students took 7 to 9 online courses, 94 (30.5%) took 4 to 6 online courses, 61 (19.8%) took 1 to 3 online courses, and only 35 (11.4%) took 10 or more online courses. All participants had experienced online course learning. In addition, 18 participants participated in the post-questionnaire qualitative interview, including

Table 1 Demographic statistics (N=308)

Subject	Option	Number	Percentage(%)
Gender	Male	145	47.3
	Female	163	52.9
Educations	Undergraduate	247	80.2
	Maters	61	19.8
Major	Humanities and arts	58	18.9
	Science	54	17.5
	Engineering	61	19.8
	Medicine	86	27.9
	Other major	49	15.9
The number of courses taken online in the past year	1~3	61	19.8
	4~6	94	30.5
	7~9	118	38.3
	≥10	35	11.4

10 males (8 undergraduates and 2 postgraduates) and 8 females (6 undergraduates and 2 postgraduates).

3.2 Measurements

A questionnaire survey and qualitative interviews were conducted in this study. The first part of the questionnaire was the scale and the second part was the demographic information. The scale includes nine variables, with 30 items. Each measurement indicator was adjusted to conform to the purpose of this study based on literature review and research purposes. Three items were refer to Davis (1989) on PU, PEOU, ATT, and BI; four items were refer to Ratna and Mehra (2015), Yakubu and Muham-madou (2020) and Davis et al. (1989) on AU; three items were refer to Cheng (2011) and Tran (2016) on SE; three items were adapted from Cho et al. (2009) on IQ, four items were refer to Li et al. (2012) on SERQ, and four items were adapted from Mailizar et al. (2021) and Rokhim et al. (2022) on SYSQ. All scales were measured using a 7-point Likert scale from 1 (strongly disagree) to 7 (strongly agree). Demographic included gender, type of education, major, and the number of courses taken online in the past year. Nine students were invited for a scale test prior to the official release of the questionnaire to identify possible problems with the language and readability of the questions and further improve the readability and comprehensibility of the scale. Semi-structured interviews were conducted after the questionnaire survey to explore the real feelings of college students about online learning. The three main three questions are: Q1. Do you think the online courses are helpful to your learning? Q2. What are your reasons for choosing online courses learning? Q3. What kind of online courses do you prefer?

3.3 Data analysis

Our research used SPSS Statistics 25 to preliminarily review the data, including Harman's single-factor test. Partial least square structural equation modeling (PLS-SEM) (Hair Jr ,et al., 2021), one of the potential programs for evaluating measurement

and structural models, was considered by Barclay et al. (1995) to be more accurate in inspections. This method modeling is applicable to theoretical development and prediction (Fornell & Bookstein, 1982). Hence, PLS-SEM was used in this study for model estimation. Based on the recommendations of Rodríguez-Ardura et al. (2020), the scale was described briefly, and an anonymous questionnaire survey was performed on students from the two colleges at different times to minimize common method variance (CMV). In addition, the impact of CMV was assessed by using Harman's single-factor test to calculate the maximum variance explained by a single factor in the model. A total of nine factors were extracted, with a cumulative explained variance of 77.416%, of which the maximum explained variance for a single factor was 25.624%, not exceeding the suggested 50% threshold (Podsakoff & Organ, 1986), indicating that there is no CMV in this study. In addition, for the semi-structured interview data, since the participants' responses were recorded using paper text, the researcher first used traditional Microsoft Word software for computerized entry of the participants' responses. Then, the questions and responses were matched one by one to sort them out. Finally, the researcher systematically analyzed each response to extract keywords, and categorized the responses into factors for analysis.

4 Result

4.1 Scale results

4.1.1 Measurement model

The measurement model was assessed by the internal consistency reliability, index reliability, convergent validity, and discriminant validity. The assessment results are as shown in Table 2. The Cronbach's alpha values for the dimensions in this study range from 0.717 to 0.918, all of which meet the standard threshold of 0.7 (Hair et al., 1998), suggesting that the internal consistency reliability of the dimension is good. The factor loadings of measurement indicators are mostly above 0.7, with only one question (BI3) at 0.629, but they all exceeded the threshold of 0.5 proposed by Fornell et al. (1981), indicating good indicator reliability. The results showed that the composite reliability values for dimensions ranged from 0.839 to 0.941 and the average variance extracted values ranged from 0.640 to 0.832. The above results exceeded the composite reliability threshold of 0.7 (Fornell & Larcker, 1981) and the average variance extracted (AVE) threshold of 0.5 (Fornell & Larcker, 1981) required for convergent validity, confirming good convergent validity. The Fornell-Larcker scale is a key indicator to assess whether a model has discriminant validity. The assessment is performed by calculating the square root of the AVE value and comparing it with the correlation coefficient between the dimensions, provided that the square root of the AVE value is larger than the correlation coefficient (Hair Jr, et al., 2021). According to Table 3, the square root of the AVE value for each dimension of this study was greater than the correlation coefficient between the dimension and other dimensions, indicating that the questionnaire of this study had good discriminant validity.

Table 2 Measurement model analysis results

Construct	Item	Mean	Standard Deviation	Factor loading	Cronbach's alpha	Composite reliability	Average variance extracted
AU	AU1	4.455	1.387	0.916	0.916	0.941	0.799
	AU2	4.591	1.334	0.907			
	AU3	4.873	1.400	0.884			
	AU4	4.620	1.354	0.868			
ATT	ATT1	5.292	1.124	0.802	0.812	0.885	0.720
	ATT2	5.377	1.119	0.858			
	ATT3	5.208	1.078	0.883			
BI	BI1	4.857	1.379	0.877	0.717	0.839	0.640
	BI2	4.656	1.273	0.870			
	BI3	4.847	1.144	0.629			
IQ	IQ1	4.935	1.209	0.869	0.918	0.937	0.832
	IQ2	4.893	1.194	0.968			
	IQ3	4.922	1.253	0.896			
PEOU	PEOU1	5.032	1.186	0.899	0.892	0.933	0.823
	PEOU2	5.055	1.213	0.906			
	PEOU3	5.010	1.249	0.916			
PU	PU1	4.906	1.104	0.792	0.798	0.881	0.712
	PU2	4.789	1.114	0.895			
	PU3	4.776	1.094	0.841			
SE	SE1	4.578	1.069	0.768	0.771	0.867	0.685
	SE2	4.555	1.113	0.836			
	SE3	4.773	1.119	0.875			
SERQ	SERQ1	4.429	1.323	0.880	0.907	0.932	0.773
	SERQ2	4.510	1.320	0.845			
	SERQ3	4.799	1.333	0.878			
	SERQ4	4.484	1.310	0.914			
SYSQ	SYSQ1	4.094	1.130	0.911	0.901	0.931	0.773
	SYSQ2	4.130	1.096	0.931			
	SYSQ3	4.133	1.161	0.898			
	SYSQ4	4.295	1.089	0.767			

Table 3 Discriminant validity using Fornell-Larcker Criterion

Construct	AU	ATT	BI	IQ	PEOU	PU	SE	SERQ	SYSQ
AU	0.894								
ATT	0.155	0.849							
BI	0.432	0.293	0.800						
IQ	0.068	0.087	0.106	0.912					
PEOU	0.351	0.346	0.396	0.031	0.907				
PU	0.321	0.280	0.439	-0.087	0.322	0.844			
SE	0.367	0.123	0.347	-0.005	0.363	0.492	0.828		
SERQ	-0.081	-0.071	-0.108	0.022	-0.124	-0.080	-0.002	0.879	
SYSQ	0.406	0.248	0.480	0.061	0.404	0.321	0.364	-0.033	0.879

Note: The bold value of the diagonal is the square root of AVE

4.1.2 Structural model

To evaluate the structural model, the path coefficients and their significance, predictive correlation (Q^2), coefficient of determination (R^2), and Goodness of Fit were assessed. The path coefficients were analyzed using the Bootstrapping Method (Hair et al., 2011) of 5000 repetitive samplings, and the path coefficients and their significant results are shown in Fig. 2; Table 4. This study also performed Stone-Geisser's Q^2 assessment to validate the predictive correlation, and when Q^2 is greater than 0, the exogenous variables have a predictive correlation (Hair Jr, et al., 2021). As shown in Table 5, Q^2 is greater than 0 for all dimensions, indicating that the model had a predictive correlation. The coefficient of determination (R^2) could be used to assess the explanatory power of research models, and Falk and Miller (1992) suggested that a model has independent explanatory power if the R^2 value of its endogenous dimension is greater than 10%. According to Table 5, the R^2 value for the actual use

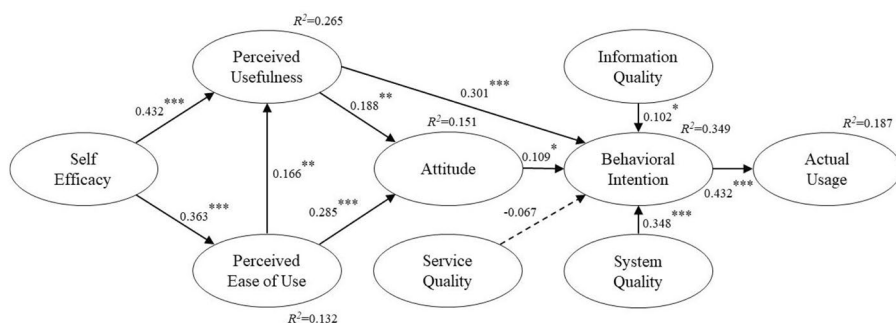


Fig. 2 Assessment Results of the Online course Learning Acceptance Mode. Note: *: $p < 0.05$; **: $p < 0.01$; ***: $p < 0.001$

Table 4 Results of research hypotheses

Hypothesis	Path	Original Sample (O)	Standard Deviation (STDEV)	T Statistics (O/STDEV)	P Values	Hypothesis testing result
H1	PU → BI	0.301	0.055	5.424	0.000	Supported
H2	PU → ATT	0.188	0.064	2.924	0.003	Supported
H3	PEOU → PU	0.166	0.059	2.797	0.005	Supported
H4	PEOU → ATT	0.285	0.056	5.100	0.000	Supported
H5	ATT → BI	0.109	0.053	2.063	0.039	Supported
H6	BI → AU	0.432	0.055	7.806	0.000	Supported
H7	IQ → BI	0.102	0.050	2.029	0.042	Supported
H8	SERQ → BI	-0.067	0.046	1.465	0.143	Not Supported
H9	SYSQ → BI	0.348	0.056	6.165	0.000	Supported
H10	SE → PU	0.432	0.055	7.842	0.000	Supported
H11	SE → PEOU	0.363	0.055	6.551	0.000	Supported

Table 5 Coefficient of determination and predictive correlation

Construct	Q ² (= 1-SSE/SSO)	R Square
AU	0.146	0.187
ATT	0.095	0.151
BI	0.204	0.349
PEOU	0.107	0.132
PU	0.179	0.265

of online courses by college students was 0.187 and the R^2 value for the behavioral intention of college students in online course learning was 0.349, indicating that the R^2 values of this study were in line with the standard, and the model has a certain explanatory power. Tenenhaus et al. (2005) suggested that a model with a goodness of fit of over 0.36 represents that the model has a good fit. A standardized root mean square residual (SRMR) of lower than 0.08 (Tenenhaus et al., 2005) also indicates a good model fit. The goodness of fit of the model in this study model is 0.404, higher than the standard of 0.36, and the SRMR value is 0.052, below the threshold of 0.08. All of these assessment results indicate that the model had a good fit.

Our research shows that PU significantly affected the behavioral intention ($\beta=0.301$, $t=5.424$, $p<0.001$) and user attitude ($\beta=0.188$, $t=2.924$, $p<0.01$), which validated H1 and H2. The PEOU directly affected users' attitude towards online course learning ($\beta=0.285$, $t=5.100$, $p<0.001$) and PU ($\beta=0.166$, $t=2.797$, $p<0.01$), which supported validates H3 and H4. This study showed that users' attitudes directly affected their behavioral intentions ($\beta=0.109$, $t=2.063$, $p<0.05$), which validated H5. The behavioral intention can predict users' actual use ($\beta=0.432$, $t=7.806$, $p<0.001$), which validated H6. The information quality ($\beta=0.102$, $t=2.029$, $p<0.05$) and system quality ($\beta=0.348$, $t=6.165$, $p<0.001$) also had a direct and significant impact on the BI, respectively, which confirmed H7 and H9. However, the SERQ has no significant impact on the BI ($\beta=-0.067$, $t=1.465$), thus H8 was not validated. In addition, this research also showed that SE had a direct positive impact on PU ($\beta=0.432$, $t=7.842$, $p<0.001$) and perceived ease-of-use ($\beta=0.363$, $t=6.551$, $p<0.001$), which supported H10 and H11.

4.2 Interview results

To gain insight into college students' opinions on online course learning, this study conducted semi-structured interviews and obtained some interesting findings. The main responses are shown in Table 6. As seen, the majority of participants indicated usefulness of online courses. Participants considered the online courses useful in terms of acquiring knowledge and developing personal learning habits. For example, Interviewee 1 (female, Master) said that the online courses had enriched her knowledge of learning methods. Interviewee 11 (male, undergraduate) said that online learning improved his English. Interviewee 18 (male, undergraduate) said, "I think online course learning is a good learning method and it has helped me to develop my consciousness to a certain extent". When it comes to the reasons for choosing online learning, some participants believed that online learning was a trend that they needed to learn to accept. For example, Interviewee 12 (male, undergraduate) felt that "This is the age of the internet and we have to learn and adapt to all kinds of learn-

Table 6 Key Answers to the Interview Questions

Question	Key answers
Q1. Do you think the online courses are helpful to your learning?	“The online courses have enriched my knowledge of learning methods” (Interviewer 2, female, master); “Online learning allows me to concentrate on the course content on the computer screen alone, making me feel very enriched” (Interviewer 3, male, master); “Online learning effectively realizes “suspended classes, ongoing learning” (Interviewer 5, male, undergraduate); “It allows me to study without geographical restrictions” (Interviewer 7, female, master); “My English has been improved through online learning” (Interviewer 11, male, undergraduate); “The online course has greatly improved my concentration and consciousness” (Interviewer 12, male, undergraduate); “There are many excellent online course learning systems available. For example, Tencent Meeting and DingTalk all help me with my studies” (Interviewer 13, female, undergraduate); “I found many useful learning resources through online learning” (Interviewer 14, female, undergraduate); “I have been taking online courses for three years and I have gained a lot, including learning methods, personal habits, and of course, the knowledge of various courses” (Interviewer 17, male, undergraduate); “I think online learning is a good learning method and it has helped me to develop my consciousness to a certain extent” (Interviewer 18, male, undergraduate).
Q2. What are your reasons for choosing online courses learning?	“I have been using computers since primary school and it is easy to operate an online course learning system” (Interviewer 1, male, undergraduate); “The online course allowed me to continue learning during the quarantine period, which was great. Everyone was using it during the pandemic” (Interviewer 2, female, master); “As required by the school” (Interviewer 3, male, master); “It’s good to take courses online during the COVID-19 pandemic” (Interviewer 6, female, undergraduate); “Online learning reduces a lot of unnecessary time, such as the time spent walking from the dorm to the classroom. It allows me to spend more time on the course study” (Interviewer 7, female, master); “Online learning is convenient, allowing me to study online while eating” (Interviewer 8, female, undergraduate); “Online course learning is a good option for me, as it helps me to avoid the stress when answering questions face to face” (Interviewer 10, female, undergraduate); “This is the age of the internet and we have to learn and adapt to all kinds of learning styles” (Interviewer 12, male, undergraduate); “Based on the arrangement, some teachers chose to use Tencent Meeting, some preferred Zoom” (Interviewer 13, female, undergraduate); “Online learning is a trend, and online learning platforms are easy to use” (Interviewer 14, female, undergraduate); “I am happy to take courses online as I can study in different places” (Interviewer 15, male, master); “I prefer to use Tencent Meeting because I often used it in classes and have been used to it” (Interviewer 17, male, undergraduate).

Table 6 (continued)

Question	Key answers
Q3. What kind of online courses do you prefer?	“Firstly, the course should be interesting, and secondly, the learning platform should be easy to use” (Interviewer 1, male, undergraduate); “Rich content, strong interaction” (Interviewer 2, female, master); “I remember when I started online learning for the first time, as I was not familiar with the learning system, I was a few minutes late to class. But now I am good at it” (Interviewer 4, female, undergraduate); “If the course content is not good, I won’t keep listening” (Interviewer 5, male, undergraduate); “If the course content is very up to date and cutting edge, I’ll be attracted” (Interviewer 7, female, master); “The teacher should teach vividly and in the form of live streaming, not recorded videos” (Interviewer 8, female, undergraduate); “It’s possible to learn theory courses online, but experimental courses can’t be implemented online” (Interviewer 10, female, undergraduate); “The online course app is easy to use now” (Interviewer 12, male, undergraduate); “If the course content is interesting, I will log in to the course learning system earlier” (Interviewer 14, female, undergraduate); “Rich content, vivid lectures by teachers, an easy-to-use online platform without lagging” (Interviewer 15, male, master); “The online course learning system is very user-friendly, such as the settings for audio and video on and off” (Interviewer 16, female, undergraduate); “No disconnection, clear voice of teachers, and clear system screen” (Interviewer 17, male, undergraduate); “The teacher should provide vivid lectures and interact with students, and the course content should include pictures, text, and videos” (Interviewer 18, male, undergraduate).

ing styles”. Some interviewees said that online learning has brought them a lot of conveniences. For example, Interviewee 8 (female, undergraduate) thought “online learning is convenient, allowing me to study online while eating”, while Interviewee 10 (female, undergraduate) said, “online course learning is a good option for me, as it helps me to avoid the stress when answering questions face to face”. However, some participants did not choose online courses because of the value they created, and they stated that they took online courses simply to follow the arrangements of the school and teachers. For example, Interviewee 3 (male, master) stated that online course learning was required by the school; Interviewee 13 (female, undergraduate) said, “Based on the arrangement, some teachers chose to use Tencent Meeting, some preferred Zoom”. When being asked about what kind of online courses they preferred, most participants focused on the content information, the teaching method of teachers, and the ease of use of the learning platforms. For instance, Interviewee 1 (male, undergraduate) said, “firstly, the course should be interesting, and secondly, the learning platform should be easy to use”; Interviewee 8 (female, undergraduate) said, “the teacher should teach vividly and in the form of live streaming, not recorded videos”; Interviewee 15 (male, master) said he preferred courses with rich content, vivid lectures by teachers, an easy-to-use online platform without lagging.

5 Discussion

5.1 Exploration of research findings

Online learning as a way of teaching needs attention. The educational benefits of online learning in the post-pandemic era cannot simply be dismissed (Fang et al., 2023). However, there were few studies to explore the factors affecting college students' online course learning behaviors. Using the TAM, this study incorporated variables of IQ, SYSQ, and SE to construct and validate an online course acceptance model. It also applied a combined method of quantitative questionnaires and qualitative semi-structured interviews. According to the results, the actual use of online courses by college students can be predicted by SE, IQ, SYSQ, PU, PEOU, ATT, and BI. In particular, self-efficacy positively affects users' perceived ease of use and perceived usefulness of online courses; users' behavioral intention is directly affected by perceived usefulness, attitudes, system quality, and information quality; perceived ease of use positively affects users' attitude and perceived usefulness; and perceived usefulness directly affects user attitude. This study is an extension and application of the TAM to provide a theoretical basis for the study of online course learning behaviors of college students, and help promote the further development of online education.

Our research showed that college students' SE had a direct positive impact on PU and PEOU. Our findings are consistent with previous studies (Huang et al., 2020; Rezaei et al., 2020). In other words, when students were confident to use technology for online learning, they tend to believe in the usefulness of online learning, thus enhancing their intention in online learning. Because of the COVID-19 pandemic, students were already used to online learning and were familiar with the operation of computers and smartphones, so that SE had a positive impact on PEOU. According to Venkatesh and Davis (1996), users who have great confidence in their ability are more acceptable of the technology. Some students found the use of technology for learning was easy (Doan, 2021), while others found it difficult to use technology to support learning (Bailey et al., 2017), as our participants said: "I have been using computers since primary school and it is easy to operate an online course learning system. (Interviewer 1, male, undergraduate)", "I remember when I started online learning for the first time, as I was not familiar with the learning system, I was a few minutes late to class. But now I am good at it. (Interviewer 4, female, undergraduate)", "I prefer to use Tencent Meeting because I often used it in classes and have been used to it. (Interviewer 17, male, undergraduate)". Therefore, SE is a major factor affecting users to take online learning (Punnoose, 2012). SE had a significant impact on PU and PEOU, which provides an opportunity for training related to the study of online courses. Educational institutions, such as colleges, or online learning system developers can provide comprehensive support to college students in taking online courses by adding training courses or special programs to enhance their capacity and confidence in using online course learning systems. This way, they can improve students' PU and PEOU for online learning systems and build positive behavioral intentions for online learning. Of course, it is also important for students

to fully leverage their self-learning capacity or confidence in online learning so that they can benefit from this new model of teaching in the future.

Research found that IQ had a positive effect on users' BI, which is consistent with the findings of Rokhim et al. (2022). Previous studies (Cheng, 2020; Joo & Choi, 2016) indicated that course quality affects learners' intention to continue learning the course. In the face of fierce competition in the education market, the quality of online courses has become particularly critical (Pham et al., 2022), as information quality can directly affect users' behavioral intentions (Rokhim et al., 2022). As our interviewees said: "If the course content is not good, I won't keep listening. (Interviewer 5, male, undergraduate)", "If the course content is interesting, I will log in to the course learning system earlier. (Interviewer 14, female, undergraduate)", "If the course content is very up to date and cutting edge, I'll be attracted. (Interviewer 7, female, master)". It can be seen that the information quality of online courses is particularly important. In addition, our study also showed that system quality significantly affected behavioral intention, which is in line with a previous study (Zhang et al., 2022). This indicates that students had expectations about learning systems and that the system's performance affected their learning of courses. When students perceive that an online course learning system meets their learning needs, the quality of the system is considered to meet the requirements, which can increase students' intention to take courses online. As our interviewees said, "The online course app is easy to use now." (Interviewer 12, male, undergraduate), "The online learning system is very user-friendly, such as the settings for audio and video on and off. (Interviewer 16, female, undergraduate)", "There are many excellent online course learning systems available. For example, Tencent Meeting and DingTalk all help me with my studies. (Interviewer 13, female, undergraduate)". Under the impact of COVID-19, students' desire for knowledge is likely to be stronger than at other times, and they focus more on the quality of the course knowledge and the learning system. Therefore, online course providers should try their best to improve the quality of the course content and the learning system to boost students' preference to learn online courses.

This study also found that PEOU had a direct positive impact on PU and ATT, and PU had a positive impact on attitude and intention to use. Therefore, it is necessary for educational institutions and teachers involved in online course learning to make students aware of the value of online course learning to improve their attitudes and behavioral intentions. As Farahat (2012) suggested, PU, user attitudes, and PEOU affect students' acceptance of online learning as they have a positive effect on users' BI. Therefore, user attitudes and PU and PEOU of online learning cannot be reduced. The only way to attract college users to online learning is to make them aware of the significance of online course learning to boost their motivation, which was also responded to positively by the interviews: "The online course allowed me to continue learning during the quarantine period, which was great. Everyone was using it during the pandemic. (Interviewer 2, female, master)", "I am happy to take courses online as I can study in different places. (Interviewer 15, male, master)", and "Online learning reduces a lot of unnecessary time, such as the time spent walking from the dorm to the classroom. It allows me to spend more time on the course study. (Interviewer 7, female, master)". As mentioned in the results, the usefulness of the online course content, the operability of the learning platform, and the interaction of the online

teachers could improve students' attitudes towards online learning and strengthen their use intention to take online courses. This study demonstrated that the intention of online learning of college courses had a positive effect on actual use, which is consistent with Chahal and Rani (2022) on the acceptance of online learning by students in India. In addition, the interest of users in a specific system had a direct impact on users' intentions (Davis et al., 1989). Our findings also show that college students' attitudes had a positive and significant impact on their BI, which echoes with Alharbi and Drew (2014). College students with a positive attitude towards online course learning were more likely to take online courses. For example, some participants said, "It's good to take courses online during the COVID-19 pandemic. (Interviewer 6, female, undergraduate)" and "I think online learning is a good learning method and it has helped me to develop my consciousness to a certain extent. (Interviewer 18, male, undergraduate)", and some believed "Online learning allows me to concentrate on the course content on the computer screen alone, making me feel very enriched. (Interviewer 3, male, master)" and "Online learning is a good option for me, as it helps me to avoid the stress when answering questions face to face. (Interviewer 10, female, undergraduate)".

5.2 Implications and limitations

This study has some theoretical and practical significance. Theoretical significance: First, this study further extended the TAM by integrating self-efficacy theory and the ISSM with external variables such as SE, SYSQ, SERQ, and IQ. Second, the online course learning acceptance model constructed and validated in this study is effective in predicting students' acceptance of online learning and provides a reference for other studies on technology acceptance. Third, this study used the TAM as the theoretical basis to empirically validate the constructed model for the online education sector with Chinese colleges as the subjects. The findings could enrich the application of the TAM and provide a reference for other scientific researchers to research the learning behaviors of Chinese college students in online course learning. In addition, this study is practically significant for teaching practice. First, it suggested that IQ, SYSQ, PEOU, and PU influence college students' intention in online courses and their actual use. System designers can thus focus on functionality, interaction, and operation to develop a highly acceptable online course learning system for students. Second, this study provided a reference for administrators and teachers of colleges and other educational institutions to facilitate online course learning and enhance students' enthusiasm and quality of learning in online courses. Third, this study also offered an insight into students' online course learning behaviors, which is conducive to making and implementing decisions related to online course learning and promoting the adoption of online course learning systems.

Our study has limitations and needs to be further improved in future studies. First, this study only sampled students from two colleges in China, the applicability to other countries or regions may be limited, and the sample size can be expanded by extending it to other countries in future studies; the sample size could be increased, especially the number of qualitative interviewees. Second, this research was conducted during the COVID-19 when all participants were required to take online courses. By

the end of the pandemic, students' perceptions and feelings about online course learning may change. Therefore, a vertical study may be tried in the future. Third, there are many factors affecting students' online learning behaviors. For example, Badali et al. (2022) pointed out that need-based motivation and interest-based motivation are also important considerations, such that academic motivation plays the most important role in students' retention rates of MOOCs'. Therefore, in future research, it is necessary to analyze students' motivation factors and the relationship between motivation factors and other factors in detail. Furthermore, In the future, more variables can be incorporated into different teaching models and methods to explore their possible impact on students' online course learning behaviors.

6 Conclusion

Online learning is a solution for teaching sustainability in unexpected situations such as the COVID-19 pandemic. To explore the factors related to college students' online course learning behavior, this study integrates the TAM, self-efficacy theory, and ISSM to propose an online course learning acceptance model, which is empirically validated using a SEM and qualitative interviews. This study found that the acceptance of online courses by college students is affected by SE, PU, PEOU, user attitude, IQ, SYSQ, and user behavioral intentions. In particular, self-efficacy positively affects users' perceived ease of use and perceived usefulness of online courses; users' behavioral intention is directly affected by perceived usefulness, attitudes, system quality, and information quality; perceived ease of use positively affects users' attitude and perceived usefulness; and perceived usefulness directly affects user attitude. The findings of this research can provide a reference for educational and technology development institutions related to online course learning and offer design inspirations for online course learning system designers in enhancing college students' acceptance and behavioral intentions regarding online course learning. This study further extended the TAM and enriched user research and theoretical construction in the education sector, and help promote the further development of online education.

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Data Availability All data generated or analysed during this study are included in this article.

Declarations

Conflict of interest There is no any potential conflict of interest in the work.

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