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Determinants of University Students' Perceived Usefulness and Behavioral Intentions toward Online Learning Applications in Chengdu, China

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Abstract

Purpose: This study explores the factors influencing perceived usefulness and behavioral intention among college students in Chengdu, China when using online learning applications. The conceptual framework proposes the causal relationship between perceived ease of use, perceived usefulness, effort expectations, performance expectations, convenience conditions, social influence, and behavioral intentions. **Research Design, Data, and Methods:** The researchers used quantitative methods (n=500) to distribute questionnaires to students from four universities in Chengdu as the target population. They are adopting multi-stage sampling methods, including purposive, stratified random, and convenience sampling. They conducted data analysis through confirmatory factor analysis (CFA) and structural equation modeling (SEM), including evaluating the effectiveness of the measurement model and testing causal relationships between variables. **Result:** While the relationship between perceived usefulness and behavioral intention was not fully supported, the other six hypotheses—perceived ease of use on perceived usefulness, perceived ease of use on behavioral intention, effort expectation on behavioral intention, performance expectation on behavioral intention, convenience condition on behavioral intention, and social influence on behavioral intention—were supported. **Conclusion:** Relevant recommendations for educators, school administrators, and app developers were made while noting that there were sample limitations to the study and that the sample could be expanded to include a wider range of samples and stages of education to be studied.

Keywords: Online Learning Applications, Perceived Usefulness, Perceived Ease of Use, Behavioral Intention

JEL Classification Code: E44, F31, F37, G15

1. Introduction

In the present digital era, online learning applications have emerged abundantly, offering significant convenience to learners. These Applications cover a wide range of disciplines and fields, so whether learners want to enhance their academic knowledge, learn a new language, master a certain vocational skill, or cultivate their hobbies, they can find the appropriate resources.

They often feature user-friendly interface designs that are easy to operate and navigate. They stimulate learners' interest and engagement through rich and diverse course formats, such as video tutorials, audio explanations, illustrated materials, and interactive tests and exercises.

Online Learning Applications also use intelligent technology to provide personalized learning advice and customized course content based on learners' progress and performance. At the same time, they are often equipped with socialized learning functions, allowing learners to exchange ideas, share experiences, and encourage each other with other students, creating a positive learning atmosphere.

In short, Online Learning Applications are reshaping the way people acquire knowledge and improve themselves, and they have become an important and indispensable tool in

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modern people's learning lives.

Students have effectively utilized fragmented time to learn anytime and anywhere, strengthened interaction with teachers and students, improved learning efficiency, interest, and effectiveness, and also gained a good learning experience (Zhang, 2019).

Information and communication technologies heavily influence education in the 21st century (Kassim, 2024). Advances in the Internet have enabled learning to take place online, which offers many advantages. Google Classroom, for example, has received positive reviews from learners around the world for its ease of use, usability, and usefulness.

The impact of online learning on higher education: 1. Accessibility: Online learning enables students to access educational resources anytime and anywhere, overcoming geographical barriers and expanding education coverage. 2. Flexibility: Online learning provides higher degrees of flexibility, empowering students to learn at a pace and time that suits them. 3. Cost-effectiveness: Online learning can be more economical than traditional education as it eliminates the requirement for physical classroom space and can cut down on travel and other associated expenses. 4. Enhance Learning Outcomes: Research indicates that online learning can be equally effective as traditional classroom instruction regarding student learning outcomes. 5. Technological advances enhance the learning experience (Kamraju et al., 2024).

The primary advantage of E-learning lies in the flexibility of time and place. They believe that E-learning eliminates the restrictions of place and time and assert that E-learning contributes to disseminating more knowledge than traditional modes of learning (Qazi et al., 2024).

Online learning is extremely flexible. Learners can start their learning journey at any time and place according to their own schedule, without the constraints of fixed schedules and classroom locations. This flexibility allows people with busy work schedules or a special pace of life to balance their studies with other matters better.

Secondly, online learning resources are plentiful and extensive. Via the Internet, learners can obtain high-quality educational resources from across the globe, encompassing a broad spectrum of disciplines, fields, and levels of specialization. Whether it is cutting-edge scientific research results or ancient cultural traditions, they can be easily found on the platform of online learning.

Online learning is more cost-effective. It reduces costs associated with transportation, accommodation, and other aspects. At the same time, many online courses are more reasonably priced than traditional face-to-face lectures. In addition, there are even a considerable number of free, high-quality learning resources available, which considerably lowers the threshold for learning and makes education and training accessible to a wider range of people.

Online learning can meet personalized learning needs. Learners can adjust their learning progress independently according to their own learning speed, interest preferences, and knowledge base, choose what to focus on, and skip the parts they are already familiar with to improve the efficiency and effectiveness of learning.

Online learning promotes the fairness of education. Whether learners are located in prosperous cities or remote villages, as long as they have a network connection, they can have access to the same high-quality educational resources. This breaks the limitations of geographic and economic conditions on educational opportunities and provides strong support for the realization of educational equity.

In summary, online learning, with its advantages of flexibility, richness, economy, personalization, and fairness, provides a more convenient, efficient, and high-quality learning path for the majority of learners!

2. Literature Review

2.1 Perceived Ease of Use

Barua and Urme (2023) the perceived usefulness of online teaching platforms is positively influenced by the perceived ease of use. Nguyen (2022) numerous studies have shown that the perceived ease of using online learning has a positive impact on the perceived usefulness of online learning. Rokhim et al. (2022), when users also have the sensation of the perceived ease of use, they will experience the advantages or perceived usefulness of using LMS; that is, perceived ease of use will affect perceived usefulness. According to TAM, research clearly states that PEOU contributes to PU and has a positive impact (Davis, 1989; Zeng & Arnold, 2014). Easier access to the system means that users can more easily access and utilize resources to gain responsive skills and knowledge. Users will likely have higher PU if they have more PEOU when using the system. Therefore, PEOU has a positive impact on PE. Based on the TAM model, the conclusion reached is that the more user-friendly the new technology, the greater the perceived usefulness, and the perceived usefulness of ICT as a learning tool is positively influenced by the perceived ease of use (Chung & Tan, 2004). Bag et al. (2022) When using an online learning system, users assess the friendliness of the platform, which means that perceived ease of use affects the perceived usefulness and the behavioral intention of students to accept the online learning system. Perceived ease of using an online education system significantly affects perceived usefulness. These investigations have resulted in the formulation of the subsequent hypothesis:

Rokhim et al. (2022) perceived ease of use impacts behavioral intention. It is argued that based on the continuous efforts of the education sector to make pedagogical innovations. The perceived ease of utilizing the system is strongly and positively associated with learners' behavioral intention to use it (Jaiyeoba & Iloanya, 2019). A study on the effect of learners' use of an online learning system discovered that perceived ease of use had a notable impact on behavioral intention (Rahman et al., 2023). The study proposes that Perceived ease of use considerably impacts behavioral intention (Davis, 1989). The perceived ease of use of e-learning was discovered to increase the likelihood of utilizing the online learning system in general, having a notable impact on their behavioral intention to use it (Mailizar et al., 2021). Perceived ease of use was discovered to have a notable impact on behavioral intention during the users' use of the system (Hossain et al., 2022). Lin (2013) observed that when users engage with u-learning, their behavioral intentions are positively influenced by perceived ease of use. Consequently, the following hypotheses have been developed:

H1: Perceived ease of use has a significant impact on perceived usefulness.

H3: Perceived ease of use has a significant impact on behavioral intention.

2.2 Perceived Usefulness

Perceived usefulness plays an important determinant of in-service teachers' behavioral intention when utilizing the system (Tumenbayar et al., 2019). Anticipating the inclination to utilize an E-learning platform: a case analysis conducted at Begum Rokeya University, Rangpur, Bangladesh, showed that perceived usefulness significantly influences the prediction of behavioral intention (Humida et al., 2022). When users perceive usefulness, they will have behavioral intention; that is, perceived usefulness influences behavioral intention (Rokhim et al., 2022). It is argued that perceived usefulness is significantly and positively correlated with behavioral intention when learners use the system based on online learning research (Jaiyeoba & Iloanya, 2019). A study based on learners' use of an online learning system found that Perceived usefulness had a significant effect on behavioral intention (Rahman et al., 2023). Perceived usefulness significantly affects behavioral intention (Davis, 1989; Davis et al., 1992). It was discovered that the system's perceived usefulness significantly impacted learners' behavioral intention (Yuan et al., 2021). Lin (2013) states that users' perceived usefulness when learning with U-learning positively influences behavioral intention when utilizing U-learning. The above research can lead to the following assumptions:

H2: Perceived usefulness has a significant impact on behavioral intention.

2.3 Effort Expectancy

Research suggests that effort expectancy arises from users' beliefs that technology use is relative and unaffected by mental effort. Thus, the expected effort strongly indicates a behavioral intention to adopt mobile learning. UTAUT proposed Effort expectancy as an indicator of real-world technology adoption; Effort expectancy is a strong indicator of behavioral intention to embrace mobile learning (Alowayr, 2022). The degree to which effort expectancy allows users to perceive the ease of technology use positively influences behavioral intention to use the technology (Venkatesh et al., 2003). It is also an important determinant of students' behavioral intention (Jaradat & Banikhaled, 2013). Research has shown a positive correlation between users' effort expectancy and behavioral intention in blended learning (Abu Gharrah & Aljaafreh, 2021). Studies have concluded that users know the direct relationship between effort expectancy and behavioral intention during blended learning (Azizi et al., 2020). The study observed a positive and direct relationship between users' effort expectancy and behavioral intention to use the system (Morton et al., 2016). Participants demonstrated a positive association between their effort expectancy and behavioral intention to use the system (Kiviniemi, 2014). Rudhumbu (2022) observed that the behavioral intention of university students to adopt blended learning was positively influenced by their perception of ease of use and effort expectancy. The following hypotheses are derived from these supported studies:

H4: Effort expectancy has a significant impact on behavioral intention.

2.4 Performance Expectancy

The study pointed out that Performance expectancy is a predictor of the actual use of the system. Performance expectancy is a strong indicator of behavioral intention to embrace mobile learning (Alowayr, 2022) and explained different constructs in their study in which Performance of the mentioned factors was deemed significant in the lives of individuals' behavioral intention utilizing the platform (Venkatesh et al., 2003). Abu Gharrah and Aljaafreh (2021) study discovered a strong association between performance expectancy and the students' behavioral intention to embrace blended learning. Amparo (2021) indicated that a direct relationship exists between performance expectancy and the behavioral intention of learning users to embrace blended learning. Abbas (2018) argued that the relationship between performance expectancy and behavioral intention is manifested by a positive relationship between performance expectancy and users' behavioral intention to embrace blended learning. Rudhumbu (2022), after a comprehensive study, it was concluded that there is a positive correlation

between performance expectancy and the behavioral intention of users to embrace blended learning. According to the information provided, the following presumptions are being made:
H5: Performance expectancy has a significant impact on behavioral intention.

2.5 Facilitating Condition

Facilitating conditions are crucial in predicting the intention to adopt M-learning, indicating a clear link between facilitating factors and behavioral intention (Venkatesh et al., 2012). A direct connection exists between facilitating condition and behavioral intention (Venkatesh et al., 2012). Abdullah et al. (2022) In their study, it was found that facilitating conditions have a positive and significant effect on the behavioral intention to adopt online learning. Abu Gharrah and Aljaafreh (2021) the facilitating condition and behavioral intention relationships have been shown to have a direct positive relationship between enabling factors and users' propensity to embrace educational platforms such as blended learning. Wu and Liu (2013) determined that there is a direct relationship between facilitating conditions and behavioral intention during blended learning among learners utilizing educational platforms. When users learn to use the system, a positive relationship exists between facilitating conditions and their behavioral intention (Lu et al., 2020). A direct relationship exists between the facilitating condition and the behavioral intention when learners are engaged in structured learning (Sattari et al., 2017). The learning system is positively associated with the user's behavioral intention to engage in learning, as facilitated by facilitating conditions (Rudhumbu, 2022). These surveys may lead to the following assumptions:
H6: Facilitating condition has a significant impact on behavioral intention.

2.6 Social influence

Behavioral intention when using a system is significantly influenced by social influence (Venkatesh et al., 2003). Social influence plays a significant role in users' awareness of their adoption of new technologies and strongly influences their behavioral intention to use the technology (Venkatesh et al., 2003). It is argued that social influence positively and significantly impacts behavioral intention to adopt online learning (Abdullah et al., 2022). A research study discovered a direct relationship between social influence and the behavioral intention of students to embrace blended learning in their behavior (Abu Gharrah & Aljaafreh, 2021). Studies have indicated a direct relationship between social influence and students' behavioral intention to embrace blended learning using the educational platform (Amparo, 2021). The use of the learning system is significantly and positively influenced by social influence. This, in turn, considerably affects users' behavioral intention to receive the system during the complex learning process (Huang & Kao, 2015). The use of learning systems for education is positively associated with the behavioral intention of students, which is influenced by social influence (Wu & Liu, 2013). The use of learning systems for education is positively associated with the behavioral intention of learners, which is shaped by social influence (Rudhumbu, 2022). The research on reference statements has led to the following assumptions:
H7: Social influence has a significant impact on behavioral intention.

2.7 Behavioral intention

Behavioral intention refers to the subjective probability that an individual will perform a specific action. For instance, if a person intends to follow a product or service, they are more likely to become an active user. In their study of the Technology Acceptance Model, Davis et al. (1989) posited that behavioral intention reflects the user’s readiness to engage in designated tasks or behaviors. Numerous empirical studies have shown that behavioral intention strongly predicts actual behavior (Zhang et al., 2018). Similarly, Kim and Niehm (2009) emphasized that behavioral intention is crucial in forecasting users’ actual behaviors. Many studies have highlighted that behavioral intention significantly influences individual acceptance of blended learning systems, demonstrating a noteworthy correlation between behavioral intention and the acceptance of blended learning (Abu Gharrah & Aljaafreh, 2021; Azizi et al., 2020; Huang & Kao, 2015).

3. Research Methods and Materials

3.1 Research Framework

Researchers carry out their research based on two fundamental theories. The two core research theories applied to conceptual frameworks include the Technology Acceptance Model (TAM) designed by (Davis, 1989) and the UTAUT, which stands for Unified Theory of Technology Acceptance and Use, proposed by (Venkatesh et al., 2003). They are integrating various research theories and relevant literature to establish a conceptual framework for evaluating the behavioral intentions and usefulness of online learning applications among students at Chengdu University. The conceptual framework of this study is shown in Figure 1.

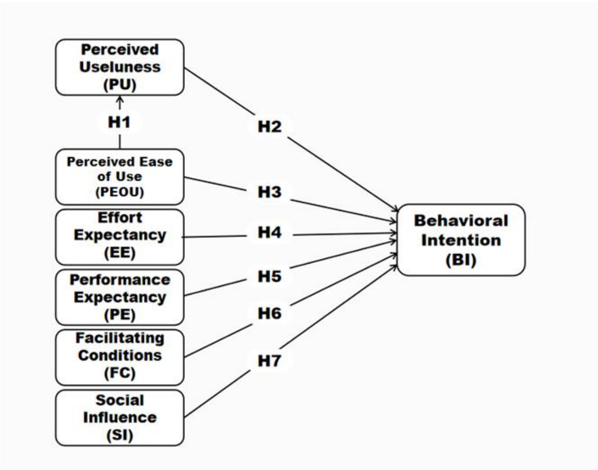

Figure 1: Conceptual Framework

H1: Perceived ease of use has a significant impact on perceived usefulness.
H2: Perceived usefulness has a significant impact on behavioral intention.
H3: Perceived ease of use has a significant impact on behavioral intention.
H4: Effort expectancy has a significant impact on behavioral intention.
H5: Performance expectancy has a significant impact on behavioral intention.
H6: Facilitating condition has a significant impact on behavioral intention.
H7: Social influence has a significant impact on behavioral intention.

3.2 Research Methodology

The study utilized quantitative research methodology to collect data from the target population through questionnaires. The target population was identified through screening questions, and a 5-point Likert scale was used to measure the proposed variables. Before data collection, the researcher used Item Objective Consistency (IOC) and Cronbach's alpha methods to establish the validity and reliability of the study. After reliability testing, the questionnaire was distributed to the target respondents, and 500 responses were accepted. After completing the data collection, the researcher analyzed the collected data through SPSS and AMOS statistics. Confirmatory Factor Analysis (CFA) was used to test the convergent accuracy and for validation. The researcher applied Structural Equation Modeling (SEM) to check the effect of variables.

3.3 Population and Sample Size

The target population comprises individuals with common attributes (Zikmund et al., 2013). Therefore, the target audience of this paper is college students from four schools with different majors who have used online learning applications in higher education institutions in Chengdu, Sichuan, China. The survey population was 500 individuals.

3.4 Sampling Technique

Probability and non-probability sampling techniques were used in this study. In the first stage, the purposive sampling method was used to select four colleges and universities in Chengdu, Sichuan Province, China. In the second stage, a stratified random sampling method was used to distribute questionnaires to college students in the four colleges. In the final stage, the convenience sampling method was chosen. This allowed access to the target respondents when the questionnaires were distributed to find out if they were the target respondents who had the time and were willing to answer the questionnaires. Respondents were screened through screening questions to determine if they met the interview requirements. The data was collected over approximately six months, from February 2024 to July 2024. The questionnaires were distributed online through "Questionnaire Star" to Sichuan University of Media and Communications, Sichuan Normal University, Sichuan Conservatory of Music, and Sichuan Conservatory of Music.

Table 1: Sample Units and Sample Size

School Name	Number of students at school	Proportional Sample Size
Sichuan University of Media and Communications	25,842	114
Sichuan Normal University	46,025	204
Sichuan Conservatory of Music	14,000	62
Chengdu University	27,000	120
Total	**112,867**	**500**

Source: Constructed by author

4. Results and Discussion

4.1 Demographic Information

The demographic target was 500 college students enrolled in 4 colleges and universities, and the findings are presented in Table 2. Male respondents accounted for 49.2%, and female respondents accounted for 50.8%. In terms of year grade, the largest percentage in this study was in the second year of college at 29.6%, followed by the third year of college at 26%, the first year of college at 23.8%, and the fourth year at 20.6%. Regarding respondents' majors, 68.6% of respondents mainly Art and Sports. This was followed by Literature and History 16.2%, Science and Engineering 13.6% and Others 1.6%.

Table 2: Demographic Profile

Demographic and General Data (N=500)		Frequency	Percentage
Gender	Male	246	49.2%
	Female	254	50.8%
Year of study	Freshman	119	23.8%
	Sophomore	148	29.6%
	Junior	130	26%
	Senior	103	20.6%
Major	Literature and History	81	16.2%
	Science and Engineering	68	13.6%
	Art and Sports	343	68.6%
	Others	8	1.6%

4.2 Confirmatory Factor Analysis (CFA)

Khan and Qudrat-Ullah (2021) noted that researchers typically test measurement models through CFA analysis techniques. The researcher tested the measurement model through the CFA analysis technique. The factor loadings have values greater than 0.30 and p-values less than 0.05. This indicates a significant correlation between the measures and the latent variables, i.e., the individual measurement items are a good reflection of the latent variables to which they belong. The structural reliability of all variables is greater than the threshold of 0.7. For example, in Table 3, the CR of Perceived Ease of Use is 0.822, the CR of Perceived Usefulness is 0.804, and so on. This means that the latent variables in the measurement model have high internal consistency, i.e., a strong correlation exists between the indicators measuring the same latent variable. The structural reliability of all variables is greater than the threshold of 0.7. This means that the latent variables in the measurement model have high internal consistency, i.e., a strong correlation exists between the indicators measuring the same latent variable. The mean-variance extracted is greater than the threshold of 0.5. This indicates that the measurement model can effectively extract the variance of the latent variables, i.e., the measurement index can better explain the variation of the latent variables.

Table 3: Confirmatory Factor Analysis Result, Composite Reliability (CR) and Average Variance Extracted (AVE)

Variables	Source of Questionnaire (Measurement Indicator)	No. of Item	Cronbach's Alpha	Factors Loading	CR	AVE
Perceived Ease of Use (PEOU)	Lin (2013)	3	0.822	0.777-0.783	0.822	0.607
Perceived Usefulness (PU)	Nedeljković and Rejman (2022)	3	0.804	0.752-0.770	0.804	0.578
Effort Expectancy (EE)	Madani et al. (2023)	4	0.870	0.715-0.866	0.872	0.633
Performance Expectancy (PE)	Devisakti and Muftahu (2023)	4	0.851	0.757-0.775	0.851	0.589
Facilitating Conditions (FC)	Rokhim et al. (2022)	3	0.813	0.747-0.794	0.815	0.595
Social Influence (SI)	Tewari et al. (2023)	4	0.849	0.749-0.784	0.849	0.584
Behavioral Intention (BI)	Rokhim et al. (2022)	4	0.852	0.761-0.780	0.852	0.591

The different latent variables can be effectively distinguished from one another. In the confirmatory factor analysis (CFA), model fit was assessed using several indicators: GFI, AGFI, NFI, CFI, TLI, and RMSEA. As shown in Table 4, the values of these indicators meet the acceptable criteria.

Table 4: Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	<5.00(Al-Mamary & Shamsuddin, 2015; Awang, 2012,)	1.042
GFI	≥0.85 (Sica & Ghisi, 2007)	0.961
AGFI	≥0.80(Sica & Ghisi, 2007)	0.950
NFI	≥0.80(Wu & Wang, 2006)	0.957
CFI	≥0.80(Bentler, 1990)	0.998
TLI	≥0.80(Sharma et al., 2005)	0.998
RMSEA	<0.08 (Pedroso et al., 2016)	0.009
Model Summary		**Acceptable Model Fit**

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

Discriminant validity was assessed by calculating the square root of the average variance extracted (AVE) and comparing it to the correlation coefficients among the variables. For adequate discriminant validity, the square root of the AVE for each variable must be greater than the correlation coefficients between that variable and the others. As shown in Table 5, the square roots of the AVE presented on the diagonal exceed the corresponding correlation coefficients, indicating strong discriminant validity among the latent variables.

Table 5: Discriminant Validity

	PEOU	PU	EE	PE	FC	SI	BI
PEOU	**0.779**						
PU	0.472	**0.760**					
EE	0.428	0.402	**0.796**				
PE	0.316	0.325	0.358	**0.767**			
FC	0.376	0.320	0.419	0.354	**0.771**		
SI	0.391	0.396	0.402	0.311	0.313	**0.764**	
BI	0.512	0.455	0.482	0.386	0.434	0.440	**0.769**

Note: The diagonally listed value is the AVE square roots of the variables
Source: Created by the author.

4.3 Structural Equation Model (SEM)

Structural equation modeling (SEM) was utilized as a statistical approach for examining causal relationships within a structural framework (Byrne, 2010). SEM is suitable for studying concurrent relationships between variables within a framework and has advantages over other statistical methods. In this study, SEM was used to analyze the research model to test the internal consistency and discriminant validity of the variables, including the test of hypothesized relationships, structural model, model fitting, and estimation of the factor structure, as shown in Table 6 for the various fit indices such as CMIN/DF = 2.969, GFI = 0.862, AGFI = 0.833, NFI = 0.871, CFI = 0.910, TLI = 0.900 and RMSEA = 0.063 are in line with the acceptable values, indicating that the structural equation modeling has a certain degree of rationality and validity.

Table 6: Goodness of Fit for Structural Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	<5.00(Al-Mamary & Shamsuddin, 2015; Awang, 2012,)	2.969
GFI	≥0.85 (Sica & Ghisi, 2007)	0.862
AGFI	≥0.80(Sica & Ghisi, 2007)	0.833
NFI	≥0.80(Wu & Wang, 2006)	0.871
CFI	≥0.80(Bentler, 1990)	0.910
TLI	≥0.80(Sharma et al., 2005)	0.900
RMSEA	<0.08 (Pedroso et al., 2016)	0.063
Model Summary		**Acceptable Model Fit**

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

4.4 Research Hypothesis Testing Result

The results in Table 7 demonstrate the results of the research hypotheses testing, where seven hypotheses were tested, where H1 proved that perceived ease of use has a significant effect on perceived usefulness, with a standardized path coefficient of 0.582 and a t-value of 10.002; H2, that is, that perceived usefulness has a substantial impact on behavioral intention was not supported, with a standardized path coefficient of 0.174 and a t-value of 2.642; and H3 - H7 verified that respectively Perceived Ease of Use, Expected Effort, Expected Performance, Convenience, and Social Influence has a significant effect on Behavioral Intentions, with standardized path coefficients ranging from 0.158 - 0.316 and t-values ranging from 3.305 - 4.714, and these results support the relevant research.

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-value	Result
H1: PEOU→PU	0.582	10.002*	Supported
H2: PU→BI	0.174	2.642	Not Supported
H3: PEOU→BI	0.316	4.714*	Supported
H4: EE→BI	0.210	4.390*	Supported
H5: PE→BI	0.158	3.305*	Supported
H6: FC→BI	0.213	4.291*	Supported
H7: SI→BI	0.210	4.327*	Supported

Note: * $p<0.05$
Source: Created by the author

The results displayed in Table 7 illustrate the outcomes of the structural equation modeling (SEM) for the proposed hypotheses regarding the relationships between perceived ease of use (PEOU), perceived usefulness (PU), behavioral intention (BI), and related constructs.

Hypotheses 1 (H1), 3 (H3), 4 (H4), 5 (H5), 6 (H6), and 7 (H7) received strong support, indicating significant positive relationships between the variables. Specifically, H1 shows that PEOU has a robust effect on PU (β = 0.582, t = 10.002), confirming that users who find a system easy to use are more likely to perceive it as useful (Davis, 1989). H3 indicates that PEOU positively influences BI (β = 0.316, t = 4.714), reinforcing that ease of use contributes to users' intentions to engage with a technology (Venkatesh & Bala, 2008).

Moreover, H4 reveals that engagement with the system (EE) significantly affects BI (β = 0.210, t = 4.390), while both personal engagement (PE) and facilitating conditions (FC) also have substantial impacts on BI (H5: β = 0.158, t = 3.305; H6: β = 0.213, t = 4.291). Lastly, H7 demonstrates that social influence (SI) plays a critical role in shaping BI (β = 0.210, t = 4.327), suggesting that the opinions of others significantly impact users' intentions (Ajzen, 1991).

However, Hypothesis 2 (H2), which suggested a direct relationship between PU and BI, was not supported (β = 0.174, t = 2.642). This finding implies that while perceived usefulness is a relevant construct, it does not directly influence behavioral intention within this specific context. Therefore, further research is needed to delve deeper into this relationship.

Overall, the results confirm the significance of PEOU and contextual factors in influencing users' behavioral intentions. These findings are in line with established theories in technology acceptance, such as those proposed by Davis (1989) and Venkatesh and Bala (2008).

5. Conclusion and Recommendation

5.1 Conclusion and Discussion

Using a sample of students from four colleges and universities in Chengdu, China, this study explores the factors influencing their perceived usefulness and behavioral intentions when using online learning applications. Through a series of research methods and data analysis, the following conclusions were drawn:

Of the seven hypotheses proposed in the study, all six hypotheses were supported except H2 (perceived usefulness has a significant effect on behavioral intention), which was not fully supported. Among them, H1 indicates that perceived ease of use significantly affects perceived usefulness, which means that students are more likely to perceive an e-learning application as helpful when the application is easier to operate and has a more user-friendly interface. For example, a learning application with concise navigation and clear operational guidelines will make students find it more useful. The significant role of multiple factors on behavioral intention, such as H3 - H7, verified the significant effects of perceived ease of use, effort expectation, performance expectation, convenience, and social influence on behavioral intention, respectively. This indicates that students' willingness to use online learning apps not only depends on the ease of use of the apps themselves but is also related to their expectation of effort invested in learning, the expectation of the apps' enhancement of learning performance, the convenience of using the apps, and the influence of people around them. For example, suppose students around them actively use a certain learning app and achieve better learning results. In that case, the willingness of other students to use the app will also be enhanced.

The results of the validation factor analysis showed that the factor loadings of the variables were high (>0.5), the composite reliability (CR) was >0.7, and the average variance extracted (AVE) was >0.4, which indicated that the validity of the measurement model was good. The high factor loadings indicate that the indicators in the measurement model can effectively reflect the latent variables to which they belong, i.e., the different measurement topics can accurately measure the concepts we want to study, such as perceived usefulness, perceived ease of use, etc., which reflects the good convergent validity. Concepts under study are independent and valid from each other without confusion. The fit indicators of the structural equation model are good: CMIN/DF is less than 5.00, GFI, AGFI, NFI, CFI, TLI, and so on meet the requirements, and RMSEA is less than 0.08, which means that the structural equation model is well fitted. These indicators show that the model fits well with the actual data, meaning the constructed theoretical model can better explain the relationship between the variables. The model has a high degree of rationality and validity, which can be used to describe and predict the real situation.

5.2 Recommendation

For educators, it is recommended that teaching content and methods be optimized. Combining perceived ease of use and usefulness, educators should adjust teaching strategies based on students' feedback on the perceived ease of use and perceived usefulness of online learning applications. For example, suppose students generally believe that a certain function of an app is not easy to operate but helpful for learning. In that case, teachers can introduce the function in detail during the teaching process to improve students' ability to use the app and better utilize the app's role as a learning aid.

It is essential to recognize and address individual differences in the use of online learning applications. Educators play a pivotal role in this, as they can provide additional guidance and training to students who need to improve in app usage. This empowers students to utilize online learning resources better and underscores the educators' responsibility to ensure that all students can benefit from online learning.

Recommendations for school administrators to rationalize resource investment. Rationally allocate online learning resources based on students' frequency of use of different online learning applications, satisfaction, and feedback on learning outcomes. For example, suppose the students of a certain major have a greater demand for a specific online learning application with good feedback. In that case, the resource input for that type of application can be appropriately increased, such as purchasing more access rights or providing relevant technical support. Strengthen technical guidance and support for online learning to ensure students can use online learning applications smoothly. This includes providing maintenance of network facilities, solving technical problems in the process of application use, etc., to minimize the problem of learning inefficiency caused by technical barriers. Create a favorable learning environment, create a campus culture and atmosphere conducive to online learning, and encourage students to use online learning applications actively. For example, online learning experience-sharing sessions and online learning reward mechanisms can be organized to stimulate students' learning enthusiasm and initiative. Reasonably arrange students' online learning time and place to avoid conflicts with other courses and activities. At the same time, provide a comfortable and quiet online learning environment, such as setting up specialized online learning classrooms or study rooms with necessary equipment and facilities.

Suggestions for online learning application developers can focus on user needs to improve the design and optimize the interface and functions. Optimize the application's interface design and function settings based on the factors found in the study that affect perceived usefulness and behavioral intention. For example, simplify the operation process to make the interface more concise and intuitive; add personalized learning functions to provide customized learning content and suggestions based on students' learning progress and preferences. Improve ease of use and usefulness, continuously improve the perceived ease of use and perceived usefulness of the application, and identify and solve problems in the application promptly through user testing and feedback collection. For example, if users give feedback that a certain function is too complex, developers should simplify and optimize it in time—personalized customization to meet diversified needs. Develop personalized learning functions and content for students of different majors and grades. For example, for science and engineering students, more experimental simulation and data processing tools can be provided; for liberal arts students, literature reading and writing assistance functions can be added. With the continuous development of educational concepts and technologies, online learning applications are continuously updated and improved to meet the growing learning needs of students and the ever-changing learning environment. For example, keep up with new teaching methods and technologies and incorporate them into the functional updates of the application.

5.3 Limitation and Further Study

Due to the limited geographic and school scope, the research sample only selected students from four colleges and universities in Chengdu, China, which may only partially represent all regions in China and students from different levels of colleges and universities. There may be differences in educational resources, cultural backgrounds, and student characteristics in different regions, which may affect the generalizability of the findings. The coverage of colleagues' majors and grades still needs to be completed. Although students of different majors and grades are covered, the sample size of certain majors or grades may be relatively small, which may not fully reflect the impact of their particularities on the research results.

Future research should consider expanding the sample scope to cover colleges and universities in different regions and levels in China, including specialized colleges and key undergraduate colleges and universities. This will provide a more comprehensive understanding of the use of Online Learning applications by different groups of students, thereby improving the generalizability and representativeness of the research results. Moreover, simultaneous research on different education stages, including primary, secondary, and higher education, could provide valuable insights into the factors influencing students' perceived usefulness and behavioral intentions toward online learning applications.

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