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Understanding Behavioral Intentions and Use Behavior of Students Towards Online Learning Systems in Jiangxi, China

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Abstract

Purpose: This research paper aims to investigate the factors impacting behavioral intentions and use behavior of students in vocational collages towards online learning systems in Jiangxi, China. The conceptual framework proposed a causal relationship among perceived usefulness, perceived ease of use, attitude, perceived behavioral control, social influence, behavioral intentions, and use behavior. **Research design, data, and methodology:** The researcher used a quantitative method (n=500) to distribute questionnaires to students. The nonprobability sampling includes judgmental sampling in selecting five vocational colleges, quota sampling in proportion of sample size, and convenience sampling in collecting data and distributing surveys by the online platform. The Structural Equation Model (SEM) and Confirmatory Factor Analysis (CFA) were used for the data analysis, including model fit, reliability, and validity of the constructs. **Results:** The results explicated that perceived usefulness, perceived ease of use, Attitude, perceived behavioral control, and social influence have a significant impact on behavioral intentions Furthermore, behavioral intentions significantly impact use behavior. **Conclusions:** Six hypotheses were proven to fulfill research objectives. Hence, future research can expand educational technology and impact school management performance, manifested as new products, services, or processes created by new technological behaviors, providing schools with a better digital environment and more convenient management processes.

Keywords : Online Learning, Social Influence, Behavioral Intentions, Use Behavior, Higher Education

JEL Classification Code: E44, F31, F37, G15

1. Introduction

Over the past few years, new online teaching models have emerged, including open courseware, flipped classroom, MOOCs, and small-scale restricted online courses (SPOC), which have encouraged colleges in different countries to expedite the growth of online teaching. Although online teaching in Chinese colleges has made considerable advancements, there are concerns about its effectiveness, such as the students' inadequate online learning experience, low satisfaction with teaching, and teaching quality, as Fu (2023) pointed out. Online education in countries such as the United States, Australia, Turkey, and South Africa is confronted with several challenges, including inadequate student autonomy in learning, digital divide, insufficient teacher information literacy, low teaching efficiency, and unsatisfactory student learning experience, among others, as highlighted by EDUCAUSE (2021). This indicates a need for a more thorough investigation into the laws and mechanisms governing the effectiveness of large-scale online education in the academic community. There are pressing practical inquiries that require answers, such as the distinctions and resemblances in the impact mechanism between online and offline education, the comprehensive effectiveness of online teaching in Chinese colleges, and the underlying incentives behind it. This investigation utilizes

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online teaching data from 5 colleges and 24532 students nationwide to establish a mechanism model for online teaching effectiveness, assesses colleges' present online teaching effectiveness, and offers recommendations to enhance effectiveness and encourage reform.

The advent of mobile networks and smart devices brought about significant social changes in the early 21st century, as Alexandersson and Limberg (2012) noted. The introduction of modern educational technology has led to the redefinition and transformation of stakeholders in the original industry domain, as highlighted by Gerhardt and Mackenzie (2018). With the internet's advent, a new learning and training model has emerged. Although computers have been utilized as supplementary teaching equipment since the 1960s, they needed to be more flexible due to linearity, as pointed out by Van Manen (1997). However, with the rise in popularity of the internet and fax machines towards the end of the 1990s (Stark & Lattuca, 1997), desktop computers became widely available in the early 1990s.

In traditional classrooms, the teacher is considered the primary source and conveyor of knowledge, and students are expected to absorb this knowledge passively. Unfortunately, this approach often neglects students' learning experience since it focuses on meeting the teachers' needs rather than those of the students. As a result, courses that lack perceptual correlation and involve passive learning tend to leave students dissatisfied. Learning, however, is an active process, and students should actively utilize the resources around them to enhance their knowledge and behavior. This requires a shift from a teacher-centered approach to a student-centered approach, where the teaching method is geared toward active learning.

Even though MOOCs are openly accessible to the public and have widespread internet connectivity, they offer participants the opportunity to interact, share, and reflect. Due to their potential to facilitate continuing education and expand access to higher education, researchers believe that MOOCs will provide innovative opportunities for all learners, regardless of their entry qualifications and educational experience, as noted by Littlejohn et al. (2015). Recently, there has been a rapid increase in publications related to MOOCs, including a diverse range of perspectives and achievements from different parts of the world, as highlighted by Liyanagunawardena et al. (2013).

Governments have utilized online learning systems to enhance the implementation of information technology (IT) in education, as Tenorio et al. (2017) noted. This approach has been successful in providing students with access to educational materials and in improving the quality of instruction. To achieve this, online learning platforms such as Zoom, Tencent Meeting, and Canvas have been implemented by governments to provide students with access to educational materials and facilitate collaboration between teachers and students. These platforms have created virtual classrooms where teachers can post assignments, provide feedback, and monitor student progress. Furthermore, these platforms have created online communities where students can interact with one another and share resources.

In contrast, developing areas such as Laos, Thailand, Taiwan, and Malaysia have only recently started adopting online learning systems, as Ho (2012) pointed out. In Vietnam, the implementation of IT in education is still in its early stages. However, the Covid-19 epidemic in early 2020 led to a significant and rapid shift from face-to-face to online learning. Initially, online learning efforts in higher education were focused on a few large colleges that acquired or upgraded their existing online learning systems.

Based on data from CITIC Intelligence Research, China's online education market we experienced significant growth from 2016 to 2020, with a compound annual growth rate of 34.5%, reaching a scale of 257.3 billion yuan in 2020. The growth is mainly attributed to the rapid development of online K12 subject tutoring and early childhood education. Despite the COVID-19 pandemic, early childhood and all-around education are still growing rapidly, while online vocational education has seen an acceleration in growth, leading to a demand-supply situation. With a substantial increase in online education users, the online education industry has great potential for market growth. Reports suggest that China's online education market was valued at 126.4 billion yuan in 2014 and is projected to reach 559.6 billion yuan in 2021. The domestic online education market is expected to continue growing with the further promotion of the education informatization strategy, and the prospects for development are optimistic. Therefore, traditional educational institutions and Internet companies are interested in entering this vast market to accelerate the implementation of online education services.

Higher vocational education is gaining more attention due to the progress of society and the optimization of talent training systems. The practicality of talent training has become a focus of concern as it is an essential component of China's higher education system. Culturing reserve talent for China's economic development is increasingly important and has received recognition and attention from society. Consequently, the rapid development of higher vocational colleges needs to address how to promote the collaborative construction of online learning resources in line with the education informatization reform in China. The incorporation of online teaching platforms into classroom teaching is crucial for achieving this goal.

2. Literature Review

2.1 Perceived Ease of Use

As a result of the study carried out by Guriting and Ndubisi (2006) noted that perceived ease of use of technology can play a significant role in determining whether a particular technology is acceptable and used. There is no doubt that ease of use is crucial to the success of the technology, as determined by Davis (1989) and Lee (2008), who defined ease of use as the extent to which users believe they can use technology without much effort. According to Mika and Sanna (2015), the importance of perceived ease of use is determined by the perceived complexity of the technology. It should be noted that perceived simplicity is an important component of the perception of behavior control, and more precisely, the perception of perceived ease is an important component of perceived complexity (Davis, 1993). As defined by Kedar et al. (2021), the term "perceived ease of use" means "the degree to which users are aware of how easy it is to use a particular system" (Kedar et al., 2021), gathered users' perspectives on the perceived ease of use of products and services.

Nakayama and Leon (2019) study have confirmed that the perceived ease of use plays a positive role in millennials' intentions to use mobile apps and has a projected effect on their intentions to use them in the future. Similarly, Al-Rahmi et al. (2018) found that students' attitudes toward using mobile phones as tools for learning can be influenced by mobile learning. It is widely acknowledged that the perception of ease of use significantly impacts attitudes and intentions toward technological and mobile learning in everyday life. Specifically, the perception of ease of use of mobile learning and technology, in general, has been identified as a crucial predictor of attitudes and intentions toward these two technologies.

Apart from perceived ease of use (PEOU), perceived usefulness (PU) is another extensively studied concept. It measures the extent to which a product or service is perceived as useful in achieving a particular goal or task (Davis et al., 2006). The initial studies on perceived usefulness were focused on computer systems. Results from these studies indicated that users' perception of a system's ease of use was related to the design of the system's user interface, prior experience with the system, and level of expertise with the system (Fu, 2023).

As Sun and Jeyaraj (2013) note, more recent studies have examined the effects of PEOU on user satisfaction and loyalty. People are more likely to be satisfied with a product or service that they find easy to use and more likely to stay loyal to it if they find it easy to use. According to Kim and Han (2020), PEOU is likely to positively affect user performance, with those who are aware of it being more likely to complete tasks correctly and on time than those who are not aware of it.

Another significant outcome of the study was that perceived ease of use was more effective in improving user performance during complex tasks, highlighting its potential as a valuable tool for enhancing user performance in such scenarios. Hence, designers and developers must consider the ease of use of their products and services during the design and development process to minimize the impact of the technology acceptance model (TAM) perception variables on behavioral intention. Bhatt (2021) also suggests that high levels of technology anxiety can reduce the influence of both perception variables of TAM on behavioral intention.

H1: Perceived ease of use has a significant impact on behavioral intentions.

2.2 Perceived Usefulness

According to Davis (1989), perceived usefulness (PU) refers to the belief of customers that using a specific system can enhance their work performance. Therefore, perceived usefulness (PU) is the extent to which someone believes using a system will improve their performance (Childers et al., 2001). In Cheng et al. (2019) study, *perceived usefulness* is defined as users' intuitive expectations about a product or service. In the context of vocational colleges, perceived usefulness (PU) refers to students' belief that using a specific learning service will significantly improve their efficiency and learning quality (Zhou, 2011). Nelson (2003) defines perceived usefulness (PU) as evaluating the benefits individuals or organizations will obtain from using technology.

Furthermore, ease of use and perceived usefulness can also impact perceptions of usefulness, meaning that users of technology that is easier to use are more likely to benefit from it (Agrebi & Jallais, 2014). According to Lee et al. (2019), perceived usefulness (PU) and perceived ease of use (PEOU) have an impact on attitudes toward mobile apps, intentions to use them, and actual use of them. Perceived usefulness refers to users' belief that using a service will lead to better outcomes.

The research also revealed that perceived usefulness (PU) has a positive and significant correlation with the intention to implement online education, and subjective norms, which complement technology awareness, play a significant role in technology adoption (Sudin & Budiarto, 2021). perceived usefulness (PU) is a crucial element of the Technology Acceptance Model (TAM), which is among the most widely used models for understanding user acceptance of technology (Davis, 1993). As previously mentioned, studies have indicated that perceived usefulness (PU) is a significant predictor of technology acceptance by users. Venkatesh and Davis (2000) conducted a study that found that the perception of a technology's usefulness is one of the main factors determining whether users will adopt it. Additionally, various studies have linked the perception of the usefulness of technology to user satisfaction, ease of use, and intent to use it.

Various factors impact the perception of a technology's usefulness, including the user's prior experiences, perceived complexity, and attitude toward it. According to Venkatesh et al. (2003), users with more prior experience with the technology tend to rate it as more useful. Therefore, perceptions of usefulness play a crucial role in users' technology acceptance. Several factors, such as acceptance, satisfaction, and intention to use, are strongly driven with perceived usefulness (Pipitwanichakarn & Wongtada, 2020). Hence, technology designers and developers need to consider making their products more useful to users. One of the essential factors that influence students' adoption of online learning is their belief that it will enhance their academic performance.

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

2.3 Perceived Behavioral Control

Perceived behavioral control (PBC) is a concept in social psychology that refers to an individual's perception of their ability to control their behavior. Their attitude towards the behavior influences an individual's intention to engage in a behavior, their perception of their control over the behavior, and subjective norms that contribute to their understanding of the concept. PBC impacts an individual's motivation to act, making it a critical component in predicting and understanding behavior.

As defined by Ajzen (1991), intention refers to a person's motivation and willingness to engage in a specific behavior. Therefore, it can be inferred that perceived usefulness, interaction requirements, perceived ease of use, and enjoyment are all critical factors that impact behavioral intention (Nathalie & Souad, 2016). Behavior control, on the other hand, pertains to an individual's confidence in their ability to carry out a specific behavior (Ajzen, 2002).

Ajzen (2002) proposes that an individual's perception of ease or difficulty in performing a behavior is influenced by their perception of behavioral control. Perceived behavioral control (PBC) refers to an individual's perception of how easy or difficult it is to engage in a behavior (John, 2013). According to Bidin and Al-Rahamneh (2020), Ajzen (1988) captures the factors beyond individual control in achieving behavioral goals. Samuel et al. (2017) defines perceived behavioral control (PBC) as the ability to control the factors influencing an individual's actions. PBC is based on an individual's past experiences, anticipated obstacles, and sequences, making it reliant on past and future experiences (Linnenbrink, 2007).

John (2013) found that their trustworthiness significantly influences the perceived behavioral control of online learners. Therefore, to succeed in this position, an individual must have a positive attitude toward the users they serve, be willing to trust them, and control their behavior. Similarly, Ajzen (2012) demonstrated that perceived behavioral control significantly impacts online learning systems in the education sector. Some researchers, such as Armitage and Conner (2001), have studied the moderation effect of behavioral control on intentions and actions.

H3: Perceived behavioral control has a significant impact on behavioral intentions.

2.4 Attitude

Fishbein and Ajzen (1975) define attitude as an earned tendency to respond positively or negatively to an object over time. According to the theory of reasoned action and planned behavior, attitude predictor of behavioral adoption intentions, as found by Akroush and Al-Debei (2015). Additionally, attitude evaluates behavior based on behavioral beliefs that determine the likelihood of behavior leading to a specific outcome (Ajzen, 1991). Asiegbu Ikechukwu et al. (2012) and other previous studies measure attitude with the approach proposed by Agarwal and Prasad (1999), which refers to an individual's affective response to new technology. Fishbein and Ajzen (1975) define attitude reaction to performing a target behavior. Weng et al. (2018) demonstrated that teachers' intention to use technology is significantly influenced by their attitude according to Shiau and Chau (2016), online vocational college users' attitudes towards online learning systems refer to their level of enjoyment of the service.

According to Bashir and Madhavaiah (2015), perceived usefulness (PU) and perceived ease of use (PEOU) determine attitude; attitude, in turn, determine intentions. Attitude refers to an individual's evaluation of behavior as favorable or unfavorable. An individual's behavioral attitudes can be influenced by their positive or negative evaluations of meaningful behaviors, affecting how they perceive the consequences of performing the behavior (Al-Debei et al., 2013).

The relationship between attitudes towards products and services and intentions to use them is studied in information system user behavior models, such as those developed by King and He (2006). According to Park et al. (2014), the online learning system emphasizes the causal relationship between attitude. Students who enroll in online programs tend to have different attitudes toward online learning depending on how they perceive it.

H4: Attitude has a significant impact on behavioral intentions.

2.5 Social Influence

Chiang (2018) define *social influence* as the effect of the presence of others, whether real, implied, or imagined, on a person's thoughts, feelings, and behavior. Social influence is a powerful force in social psychology that can result in conformity, compliance, or obedience. Zhao et al. (2017) define *social influence* as a measure of how important others are to an individual, using a system to do so. Individuals adjust their attitudes or behaviors about the attitudes or behaviors of others as a result of their interaction in a social system (Leenders, 2002).

According to Zhou (2011), perceived control and social influence can influence an individual's likelihood of using an information system. Riquelme and Rios (2010) define *social influence* as the degree to which individuals use technologies when they receive feedback from colleagues, friends, family, and relatives. Social influence affects user behavior in the education sector similarly to other industries, implying that students must select their higher education institution carefully. Several studies have examined the impact of social influence on an individual's decision-making abilities when selecting a university (Kropp et al., 2005; Mangleburg et al., 2004; Mourali et al., 2005).

Ali et al. (2018) discovered that social influence impacts discontinuance behavior and social network fatigue. Social influence refers to how others influence a person's behavior, beliefs, and attitudes. Kelman (1958) proposed three dimensions of social influence: internalization, identification, and compliance.

H5: Social influence has a significant impact on behavioral intentions.

2.6 Behavioral Intentions

According to Ajzen (1991), behavioral intention refers to a user's readiness to perform a specific behavior or action. The term was initially defined by Ajzen and Fishbein in 1980 as the likelihood that a customer would adopt a technology. Belanche et al. (2012) consider the inclination of individuals to act in certain ways as a type of behavioral intention. In essence, behavioral intention reflects the willingness of an individual to engage in a specific activity (Sripalawat et al., 2011).

Behavioral intentions are a vital concept in studying human behavior, as emphasized by Eyun (2012), who consider them a significant predictor of behavior. When considering engaging in a specific behavior, behavioral intentions refer to conscious plans and goals. Research in psychology has demonstrated that intention is a robust predictor of whether a person will perform a behavior. According to Ajzen and Fishbein (1980) Theory of Reasoned Action, attitudes, and subjective norms influence people's behavioral intentions.

Several studies have analyzed the factors influencing students' intentions to enroll in online learning programs. Bag and Omrane (2020) argue that the methodology for studying behavioral intentions among students in higher education needs to be modified to reflect their adaptation to technology-oriented education systems better. Thus, behavioral intention directly impacts users' online learning behavior, as proposed below:

H6: Behavioral intentions have a significant impact on use behavior.

3. Research Methods and Materials

3.1 Research Framework

Clark and Ivankova (2016) developed a conceptual framework to organize their research and guide their investigation. A conceptual framework can be used in research to illustrate how various factors or variables will interact. This framework can be presented in written or visual form and draws on existing studies related to the research topic. It allows researchers to organize their ideas and establish clear connections between them. This research used previous literature to summarize and identify relevant variables and presented them in Figure 1.

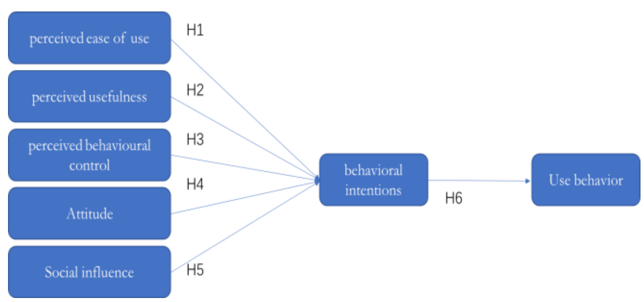

Figure 1: Conceptual Framework

H1: Perceived ease of use has a significant impact on behavioral intentions.

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

H3: Perceived behavioral control has a significant impact on behavioral intentions.

H4: Attitude has a significant impact on behavioral intentions.

H5: Social influence has a significant impact on behavioral intentions.

H6: Behavioral intentions have a significant impact on use behavior.

3.2 Research Methodology

The researcher utilized a quantitative research design to collect and analyze numerical data in their study. The research was conducted among middle to top-management students in the top five vocational colleges in Jiangxi, China, with surveys distributed online and on paper. The survey consisted of three parts to identify the key factors significantly influencing student behavioral intentions. The first step involved screening questions to determine respondents' characteristics, then rating seven proposed variables on a Likert scale ranging from strong disagreement to strong agreement. Secondly, demographic questions, such as gender, age, and education, were included to analyze all six hypotheses. Moreover, at last, A significant number of respondents were also questioned about their expert ratings of the item-objective congruence (IOC) index and the pilot test.

For validity and reliability testing, Cronbach's Alpha method was used. The questionnaire's reliability was assessed through an initial test, including both an Index of Item-Objective Congruence (IOC) evaluation and a pilot test. The IOC analysis involved three experts rating each scale item, with all items receiving a score of 0.6 or higher. Additionally, a pilot test involving 50 participants was conducted, and the reliability was measured using the Cronbach alpha coefficient. The results indicated that all questionnaire items exhibited strong internal consistency, with a reliability score of 0.7 or greater (Sarmento & Costa, 2016).

After the reliability test, 500 responses were received from the target respondents. SPSS AMOS 27.0 was used to analyze the collected data. Confirmatory Factor Analysis (CFA) was then performed on the data to ensure convergence accuracy and validation. The model fit measurement was calculated using the overall test with given data to ensure model validity and reliability.

3.3 Population and Sample Size

Five vocational colleges in Jiangxi were chosen to represent this study's population. The students are during second to third year and have been using online learning system. Each variable will be examined to determine its relationship with the other. A multistage sampling method, including judgmental sampling, will be used to select the sample size. (Kline, 2011) suggests a sample size of at least 500 respondents for Structural Equation Models. Five hundred respondents took the survey. Data screening led to the use of 500 responses in this study.

3.4 Sampling Technique

The nonprobability sampling includes judgmental sampling in selecting five vocational colleges, quota sampling in proportion of sample size, and convenience sampling in collecting data and distributing surveys by the WenJuanXing platform. Table 1 shows the number of students the researcher needs to select from each college according to sample size and student proportion.

Table 1: Sample Units and Sample Size

College Name	Population Size	Proportional Sample Size
Jiangxi Tourism and Commerce Vocational College	6788	138
Jiangxi Vocational and Technical College of Communications	5432	110
Jiangxi Modern Polytechnic College	6322	129
Jiangxi Vocational Technical College of Industry & Trade	2134	44
Jiangxi Institute of Economic Ad ministrators	3856	79
Total	**24532**	**500**

Source: Constructed by author

4. Results and Discussion

4.1 Demographic Information

The profile of the demographic targets 500 participants and is concluded in Table 2. Male respondents represent 47.6%, and female respondents account for 52.4%. For the year of study, there were 148 sophomore students accounted for 29.6% percent, 305 junior students accounted for 61% percent, and 47 senior students accounted for 9.4%.

Table 2: Demographic Profile

Demographic and General Data (N=500)		Frequency	Percentage
Gender	Male	238	47.6%
	Female	262	52.4%
Year of Study	Sophomore	148	29.6%
	Junior	305	61%
	Senior	47	9.4%

Source: Constructed by author

4.2 Confirmatory Factor Analysis (CFA)

Confirmatory Factor Analysis (CFA) was conducted in this study. It is a statistical technique that can identify and investigate hypothetical constructs that appear reliable but are not. The general equation of CFA involves analyzing detailed hypotheses in a deductive manner, making it different from other approaches to analyzing hypothetical constructs (Hoyle, 2012). The results indicated that all constructs have strong internal consistency, with a reliability score of 0.7 or greater (Sarmento & Costa, 2016). Table 3 demonstrates that the Cronbach's Alpha values exceeded 0.7, indicating strong internal consistency. Additionally, the composite reliability (CR) surpassed 0.70, affirming the reliability of the measurements. The average extracted variance (AVE) values also exceeded 0.50, suggesting robust convergent validity. Furthermore, the factor loading values were all above 0.50, further supporting the validity of the factors. The significance of factor loading of each item and acceptable values indicate the convergent validity (Hair et al., 2006). Thus, all estimates are significant.

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	Madhurima and Ewuuk (2014)	4	0.841	0.686–0.83	0.834	0.558
Perceived Usefulness	Buabeng-Andoh (2018)	4	0.864	0.767–0.81	0.879	0.645
Perceived Behavioral Control	Moorthy et al. (2017)	4	0.863	0.752–0.82	0.867	0.621
Attitude	Oertzen and Schröder (2019)	4	0.821	0.647–0.869	0.828	0.551
Social Influence	Thakur and Srivastava (2014)	5	0.876	0.712–0.828	0.886	0.610
Behavioral Intentions	Moorthy et al. (2017)	4	0.817	0.573–0.794	0.811	0.519
Use Behavior	Kim and Kwahk (2007)	4	0.846	0.721–0.809	0.845	0.577

The square root of the average variance extracted is determined that all the correlations are greater than the corresponding correlation values for that variable as of Table 4. In addition, GFI, AGFI, NFI, CFI, TLI, and RMSEA are used as indicators for model fit in CFA testing.

Table 4: Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	< 5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	4.062
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.825
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.819
NFI	≥ 0.80 (Wu & Wang, 2006)	0.825
CFI	≥ 0.80 (Bentler, 1990)	0.861
TLI	≥ 0.80 (Sharma et al., 2005)	0.842
RMSEA	< 0.08 (Pedroso et al., 2016)	0.078
Model Summary		**In harmony with empirical data**

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

The convergent and discriminant validity was verified as the study value shown in Table 5 are greater than acceptable values. Therefore, convergent validity and discriminant validity are ensured. Moreover, these model measurement results consoled discriminant validity and validation to measure the validity of subsequent structural model estimation.

Table 5: Discriminant Validity

	PEOU	PU	PBC	AT	SI	BI	UB
PEOU	**0.747**						
PU	0.220	**0.803**					
PBC	0.199	0.234	**0.788**				
AT	0.168	0.323	0.219	**0.742**			
SI	0.233	0.179	0.207	0.304	**0.781**		
BI	0.420	0.400	0.407	0.448	0.461	**0.760**	
UB	0.437	0.470	0.380	0.467	0.511	0.524	**0.720**

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

4.3 Structural Equation Model (SEM)

According to Hair et al. (2010), Structural Equation Modeling (SEM) validates the causal relationship among variables in a proposed model and encompasses measurement inaccuracy in the structure coefficient. The goodness of fit indices for the Structural Equation Model (SEM) is measured as demonstrated in Table 6. The model fit measurement should not be over 3 for Chi-square/degrees-of-freedom (CMIN/DF) ratio, and GFI and CFI should be higher than 0.8 as recommended by Bentler (1990). The calculation in SEM and adjusting the model by using SPSS AMOS version 27, the results of the fit index were presented as a good fit, which are CMIN/DF = 3.558, GFI = 0.851, AGFI = 0.824, NFI = 0.841, CFI = 0.880, TLI = 0.868 and RMSEA = 0.072, according to the acceptable values are mentioned in Table 6.

Table 6: Goodness of Fit for Structural Model

Index	Acceptable	Statistical Values
CMIN/DF	< 5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	3.558
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.851
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.824

Index	Acceptable	Statistical Values
NFI	≥ 0.80 (Wu & Wang, 2006)	0.841
CFI	≥ 0.80 (Bentler, 1990)	0.880
TLI	≥ 0.80 (Sharma et al., 2005)	0.868
RMSEA	< 0.08 (Pedroso et al., 2016)	0.072
Model Summary		**In harmony with empirical data**

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

Table 7 shows that regression or standard path coefficients supported five out of six proposed hypotheses. Regression coefficients measure the magnitude of correlation among the independent and dependent variables. Based on Perceived ease of use (PEOU), Perceived behavioral control (PBC), and Perceived usefulness (PU), Use Behavior (UB) was strongly influenced by Behavioral intention (BI).

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-Value	Result
H1: PEOU →BI	0.313	6.269***	Supported
H2: PU→BI	0.334	6.942***	Supported
H3: PBC→BI	0.247	5.341***	Supported
H4: AT→BI	0.281	5.529***	Supported
H5: SI→BI	0.416	8.196***	Supported
H6: BI→UB	0.565	8.686***	Supported

Note: *** p<0.001
Source: Created by the author

The result from Table 7 can be refined that:

H1 has proven that Perceived ease of use (PEOU) is one of the key drivers of Behavioral intention (BI), with a standard coefficient of 0.313 for the structural pathway. According to Fu (2023), perceived ease of use (PEOU) can increase users' behavioral intentions (BI). The college must offer the appropriate Perceived Ease of Use (PEOU) level to drive students to learn effectively and efficiently. In terms of **H2**, the analysis outcome supported the hypothesis that Perceived usefulness (PU) had a significant impact on students' Behavioral intention, with a standard coefficient value of 0.334 supporting this conclusion. Based on Fu (2023), the perception of usefulness among individuals can influence students' behavior in creating knowledge and ideas during learning time. It has been posited in **H3** that Perceived Behavioral Control (PBC) has a significant impact on Behavioral Intention, and the standard coefficient value is 0.247 As perceived behavioral control is believed to influence an individual's motivation to act, it is regarded as a critical factor for understanding and predicting behavior, encouraging students to perform at their best. Behavioral intention (BI) showed the strongest significant impact on perceived behavioral control (PBC) in this study, consistent with previous literature. Behavioral intention is also closely related to attitude (AT), with a standardized path coefficient of 0.281 and a t-value of 5.529*** (**H4).** Attitude is a significant with the degree of perceived usefulness of an online learning system. Social influence (SI) strongly impacts behavioral intention (BI). According to Zhao et al. (2017), social influence (SI) and behavioral intention (BI) are correlated with a standardized path coefficient of 0.416 in **H5.** Another important attribute of the usefulness of an online learning system is its ability to influence students' conformity, compliance, or obedience.

As a final point, the standard coefficient of Behavioral intention (BI) on Use Behavior (UB) revealed a value of 0.565, which confirmed the significance of **H6**. As a result of the Behavioral intention (BI) support in the study, the student's Use Behavior (UB) significantly influences since the student is comfortable and useful for efficiently gathering information to complete the task.

5. Conclusion and Recommendation

5.1 Conclusion and Discussion

This study aimed to examine the factors affecting vocational students' behavioral intentions and the use of the Online Learning System in Jiangxi, China. Based on the research questions defined, the researcher has proposed six hypotheses to examine the effects of perceived ease of use (PEOU), perceived usefulness (PU), perceived behavioral control (PBC), attitude (AT), and social influence on behavioral intention to use online learning systems. In the study, students from five vocational higher education colleges in Jiangxi, China, were targeted as participants who had studied online. A multistage sampling procedure was used to select the colleges in Jiangxi, which began with judgmental sampling. A stratified random sampling procedure was used to allocate the sample size proportionately to each college, followed by convenience sampling to distribute the questionnaires. As a tool, a questionnaire was used to collect quantitative data. The questionnaire contained screening questions, measuring all variables using a five-point Likert scale from strongly disagree (1) to agree (5) strongly, and the demographic question of respondents. Prior to larger group distribution, the reliability and consistency of each measurement item were ensured by conducting an Item-Objective Congruence (IOC) with three experts and a pilot test with fifty sample respondents. The questionnaires were distributed online at 500 sets to undergraduates with online learning experiences from the selected colleges in Jiangxi. With the collected data, Confirmatory Factor Analysis or CFA was adopted to measure and test the validity and reliability of the research conceptual model. Various convergent validity measures were applied to the research conceptual model, including composite reliability, Cronbach's alpha reliability, factor loading, average variance extraction, and discriminant validity. As part of the research, structural equation modeling was also utilized to analyze and discuss the factors that affect vocational students' use behavior and behaviors toward online learning systems. The following findings were described in the study.

Firstly, social influence (SI) was students' strongest predictor of behavioral intention. Behavioral intention significantly influences Use Behavior (UB). The previous literature of Aaker and Maheswaran (1997) confirmed the relationship between social influence (SI) and Use Behavior (UB). Therefore, expanding the influence of the online system's sociality and advantages is vital for motivating behavioral intention.

Secondly, Perceived usefulness (PU) also impacts behavioral intention. Perceived usefulness is the users' evaluation to a certain extent of the utility of new IT, such as performance based on a target related, which affects behavioral intention in a significant way. Furthermore, Perceived ease of use (PEOU) was also an important factor impacting behavioral intention.

Last, Bag and Omrane (2020) posited that Behavioral intention significantly influences Use Behavior (UB) when there is a tenacious establishment and expression, a strong willingness and persistence to complete academic work, a desire, love, and pride in learning, as well as a complete focus, obsession, and deep immersion in executing course tasks.

5.2 Recommendation

The researcher identified key factors of Perceived ease of use (PEOU), Perceived usefulness (PU), Perceived behavioral control (PBC), Attitude (AT), and social influence (SI) impacting behavioral intention (BI) and Use Behavior (UB) to online learning system on the five vocational colleges in Jiangxi, China.

The above important factors should be developed and promoted to gain intention to adopt online learning systems in vocational colleges except for trust due to its insignificant. In this research, social influence (SI) is the strongest predictor of behavioral intention to use online learning systems. Hence, the behavioral intention of the system to use Behavior is the key influence and must be emphasized. It implies that students can adopt an online learning system if they consider it a useful tool to enhance their vocational performance. The developer of the course system, teachers, and top management of vocational colleges should ensure that the attributes of Perceived ease of use (PEOU), Perceived usefulness (PU), Perceived behavioral control (PBC), Attitude (AT) are available when using online learning system. The features provided by online learning systems should be responsive, flexible, accurate, and relevant to their studies. The feature should include quality technical assistance, so sufficient training should be conducted to improve the service level of practitioners' practical ability, to help learners more effectively learn online courses to improve learners' willingness to accept online learning systems. Once the quality features are ensured, the system's usefulness, operation procedures, and other facilities supported should be promoted to the students, such as training or media communications for their awareness and recognition.

5.3 Limitation and Further Study

The limitation of the study lies in the fact that, based on the scale of education, population, and sample size, specialized vocational students from five vocational colleges in Jiangxi, China. Different analysis results may appear when investigating the size, majors, level of education informatization, or teaching level of different colleges. Further research can be conducted on other structures that may affect the behavior of modern educational technology, such as perceived organizational support, team learning, self-learning, knowledge trust, etc. In addition, future research can expand educational technology and impact school management performance, manifested as new products, services, or processes created by new technological behaviors, providing schools with a better digital technology environment and more convenient management processes.

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