pISSN: 1906 - 6406 The Scholar: Human Sciences
eISSN: 2586 - 9388 The Scholar: Human Sciences
http://www.assumptionjournal.au.edu/index.php/Scholar

Examining on Behavioral Intention and Use Behavior of Students Online Learning Systems: A Case of Vocational Collages in Jiangxi, China

Xiong Wei*

Received: August 24, 2023. Revised: October 12, 2023. Accepted: October 13, 2023.

Abstract

Purpose: This research paper aims to examine the factors impacting vocational collages' students' behavioral intention and use behavior of the online learning system 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 the quantitative method (n=500) to distribute questionnaires to students. The nonprobability sampling includes judgmental, quota sampling, and convenience sampling in collecting data and distributing surveys by the online survey 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, and perceived behavioral control have a significant impact on behavioral intentions. In addition, behavioral intentions significantly impact use behavior. Nevertheless, social influence has no significant impact on behavioral intentions. **Conclusions:** Six hypotheses were proven to fulfill research objectives. Hence, it is recommended that teaching management departments and educational technology centers provide assessments to measure the level of influence and teaching development plans to enhance the overall level of teaching information in the school.

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

JEL Classification Code: E44, F31, F37, G15

1. Introduction

In recent years, new online teaching models, represented by open courseware, flipped classrooms, MOOCs, and small-scale restricted online courses (SPOC), have sprung up, continuing to promote universities in various countries to accelerate the development of online teaching. The introduction of mobile networks and smart devices in the early 21st century triggered significant social changes (Alexandersson & Limberg, 2012). Incorporating education technology into traditional industry domains has led to the redefinition and transformation of stakeholders (Gerhardt & Mackenzie, 2018). The emergence of the internet has given rise to a new training and learning model. Although computers have been used as auxiliary equipment for teaching since the 1960s, their linearity made them inflexible. However, the popularity of the Internet and fax machines grew in the late 1990s (Stark & Lattuca, 1997), and desktop computers became widely available in the early 1990s. Governments have adopted online learning systems to incorporate modern technology into education and provide educational materials to students (Tenorio et al., 2017). This approach has not only enabled students to access educational materials but has also led to enhanced instruction quality. Governments have implemented online learning platforms such as Zoom, Tencent Meeting, and Canvas to facilitate access to educational materials and enable students to collaborate with teachers. These platforms have created virtual classrooms where teachers can post assignments, provide feedback, and monitor student progress.

1*Xiong Wei, School of Arts media and computer, Jiangxi tourism and commerce vocational college, China. Email: 3844377@qq.com

Additionally, these platforms have been used to create online communities, enabling students to interact with each other and share resources. This reflects the need for more in-depth research on large-scale online teaching operation laws and effectiveness mechanisms in the academic community. In Chinese vocational colleges, what is the overall effectiveness of online teaching? What are the underlying motivations behind it? What is the impact mechanism of online teaching? All of these questions require urgent, practical answers. As part of this study, online teaching research data was collected from 5 vocational colleges and 45266 associate degree students nationwide, the mechanism model was constructed for online teaching effectiveness, the effectiveness of online teaching at colleges was analyzed, and recommendations for improving effectiveness were provided.

Due to the appearance of mobile networks and smart devices, the early 21st century saw dramatic social changes (Alexandersson & Limberg, 2012). Especially with the introduction of information technology (IT), stakeholders in the original industry domain are redefined and transformed (Gerhardt & Mackenzie, 2018). A new model for training and learning has been established since the internet was introduced. According to Van Manen (1997), computers were used in teaching as auxiliary equipment as early as the 1960s but were not flexible due to linearity. The Internet and fax machines gained popularity as the 1990s ended (Stark & Lattuca, 1997), and desktop computers were readily available in the early 1990s.

The teacher is regarded as the primary source and transmitter of knowledge in traditional classrooms, while students are expected to absorb knowledge as if they were sponges. Students' learning experience is neglected as "focusing on teachers' needs" and "transferring knowledge, skills, and experience" are ignored; most courses that make students feel dissatisfied have the characteristics of passive learning and no perceptual correlation. Learning is an active process. Students should use the resources around them to improve their knowledge and behavior and turn passive learning into active learning. This requires the teaching method to change from teacher-centered to student-centered.

Despite its open nature, MOOCs are publicly accessible and have ubiquitous Internet connections, enabling participants to interact, share, and reflect. Given its potential to facilitate continuing education and expand access to higher education, the researchers hope it will provide innovative opportunities for all learners, regardless of entry qualifications and educational experience (Littlejohn et al., 2015). In recent years, MOOC-related publications have rapidly increased, including diverse perspectives and achievements worldwide (Liyanagunawardena et al., 2013).

In order to improve modern technology implementation in education, Online learning system has been used by governments to provide educational materials to students. (Tenorio et al., 2017). This approach has successfully provided students with access to educational materials, but it has also been used to improve the quality of instruction. Governments have implemented online learning platforms such as Zoom, Tencent Meeting, and Canvas to provide students with 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. Additionally, these platforms have been used to create online communities where students can interact with each other and share resources.

In contrast, in developing areas (including Laos, Thailand, Taiwan, and Malaysia), online learning system has only recently been embraced (Ho, 2012). It is still in its infancy in Vietnam to implement IT in education. In early 2020, the Covid-19 epidemic catalyzed a strong and drastic transition from face-to-face to online learning. The initial efforts to implement online learning in higher education were concentrated in a few large colleges that purchased online learning systems (OLS) or upgraded existing online learning systems.

According to statistics from CITIC Intelligence Research, 2020, the scale of China's online education market has reached 257.3 billion yuan, and the compound annual growth rate is 34.5% from 2016 to 2020. This growth is largely attributed to the accelerated development of online K12 subject tutoring and early childhood education tracks. Despite the epidemic in full swing, early childhood and all-round education continue to grow vertically. In vocational education, online growth has been accelerating, resulting in a supply-and-demand situation. With the rapid growth of online education users, there is a large market potential and great prospects for growth in the online education industry. Relevant reports show that in 2014, the online education market size in China was 126.4 billion yuan, reaching 559.6 billion yuan by 2021. Under the further promotion of the education informatization strategy, the domestic online education market will continue to grow, and its development prospects are relatively optimistic. At the same time, the large market is drawing in many traditional educational institutions and web-based companies to speed up the implementation of online education services.

With the progress of society and the optimization of the personnel training system, more attention is paid to higher vocational education. As a crucial part of the Chinese higher education system, the practicability of personnel training has also become the focus of attention. The economic construction of our country's backup talent cultivation also plays an increasingly critical role and has gained the attention of society and the masses. Therefore, following the overall planning of China's education Informa ionization reform, the rapid development of higher vocational colleges urgently needs to solve how to promote the collaborative construction of online learning resources. In order to achieve this goal, it is crucial to incorporate the use of online teaching platforms into classroom teaching.

2. Literature Review

2.1 Perceived Ease of Use

Perceived ease of use refers to how easily an innovation is perceived in terms of learning, using, or understanding it, as defined by Rogers (1962) and Davis (1989). It can also refer to an individual's perception of how quickly they can comprehend the technology, according to Zeithaml et al. (2002). In numerous studies, perceived ease of use has been used to mediate the impact of other variables on behavioral intentions (Lu, 2014).

The perception of ease of use is a critical construct in the technology acceptance model, including TAM and C-TAM-TPB (Kim & Kwahk, 2007), as it is an essential aspect of the post-adoption experience of m-commerce usage. Generally, perceived ease of use is less crucial than perceived usefulness in contributing to continuity intentions. It has consistently been shown to influence post-adoption use directly (Taylor & Strutton, 2010) or jointly affect perceived usefulness (Liu & Forsythe, 2010; Zhou, 2011).

Behrend et al. (2011) demonstrated that the perception of ease of use is related to the intention to use mobile learning. In terms of perceived ease of use, student users perceive their ability to start, learn, run, and share online learning applications at any time and from any location, as well as access, synchronize, and share their resources and documents from anywhere and anytime. As a result, they are more likely to use that mobile learning provider. For a vocational learning environment to be perceived as useful, it must be perceived as easy to use (Shiau & Chau, 2016).

According to Arpaci (2016), the perceived ease of use of mobile learning positively impacts users' perception of its usefulness. Online learning systems benefit users due to their simplicity of operation, efficiency of synchronous sharing function, and ease of use in completing knowledge construction. It has also been discovered that perceived ease of use positively and significantly impacts vocational students' perception of online learning's usefulness and their intention to use it (Wang et al., 2016). Thus, a hypothesis is proposed:

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

2.2 Perceived Usefulness

Perceived usefulness is defined by Davis (1989) as the degree to which an individual believes that using an innovation will enhance their study performance, based on the word useful, meaning the ability to be used advantageously. Mathwick et al. (2001) defined perceived usefulness similarly to Davis (1989), measuring how a system can improve an individual's role performance. Perceived usefulness has been found to have a highly significant relationship with the adoption of e-learning and m-learning. Technology acceptance research is critical, especially for e-learning and m-learning. Anckar et al. (2002) discovered that perceived usefulness greatly influences e-learning in Finland, consistent with Nysveen et al. (2005) research on e-learning in Norway, which found perceived usefulness to be significant.

In the studies of Crabbe et al. (2009), Khalifa and Shen (2008), and Wu and Wang (2006), perceived usefulness was also found to have a significant impact on e-learning use. Perceived usefulness has also been applied to mobile learning in numerous studies. Akturan and Tezcan (2012) examined the adoption of mobile learning by young Turks in 2012, and e-learning adoption showed the same trend, with perceived usefulness significantly influencing m-learning adoption. In previous studies, technology acceptance is heavily influenced by numerous significant factors. Despite the findings of Mallat et al. (2009) and Amin et al. (2008), they found no significant association between perceived usefulness and innovation adoption in Malaysia.

The user's attitude towards technology, prior experiences with it, and perception of its complexity can all impact their perception of its usefulness. Venkatesh et al. (2003) found that users with more experience with the technology had higher levels of perceived usefulness. The literature suggests that perceived usefulness is crucial in user acceptance of technology. Many factors affect user acceptance, satisfaction, and intention to use technology, which is strongly related (Pipitwanichakarn & Wongtada, 2020). Therefore, technology designers and developers need to consider increasing users' perceived usefulness of their products. Additionally, the belief that online learning can enhance a student's academic performance is one of the elements that can influence their likelihood of using it. Thus, a hypothesis is proposed:

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

2.3 Perceived Behavioral Control

Ajzen (2002) explains that perceived behavioral control refers to an individual's perception of the ease or difficulty of implementing a particular behavior rather than the actual level of control over it. This concept involves evaluating and weighing the possible barriers, restraints, or struggles that may arise while performing the behavior about an individual's skills, abilities, opportunities, and resources (Ajzen, 1991). This study defines perceived behavioral control as the perception of ease or difficulty in performing online learning behaviors.

Perceived behavioral control directly influences behavioral intention across various contexts, including various education resources (Bolduc & Kinnally, 2018). It is hypothesized that online learning users who believe they possess the necessary skills, resources, and opportunities to participate in online learning behaviors are more likely to have a strong intention to participate in these activities as they perceive themselves to have control over the behavior.

Ajzen (1991) propose that perception plays a significant role in determining the level of difficulty or ease in performing a particular behavior, while perceived behavioral control refers to an individual's perception of the ease with which they can perform a behavior based on their perception of the ease with which it can be performed. According to Bidin and Jomaa (2019), Ajzen (1988) has identified perceived behavioral control as one factor that influences behavior, in addition to an individual's authority. Samuel et al. (2017) further suggest that perceived behavioral control refers to an individual's ability to control the factors that may influence their actions, which is also influenced by past experiences, anticipated obstacles, and sequences of events (Linnenbrink, 2007).

A study by John (2013) found that the trustworthiness of interactions between users strongly influences perceived behavioral control of online learning systems. An individual must have a positive attitude towards the users they serve, be willing to trust them and be capable of controlling their behavior. Therefore, Ajzen (2012) suggest that perceptions of behavioral control significantly impact online learning systems in the learning sector. Armitage and Conner (2001) have researched the moderating effect of behavioral control on intentions and actions. Thus, a hypothesis is proposed:

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

2.4 Attitude

According to Fishbein and Ajzen (1975), attitude refers to an individual's overall perception of a stimulus object as favorable or unfavorable. It can also refer to an individual's opinion about something, which reflects their level of support for it (Huang, 2016). Davis (1989) stated, an individual's attitude towards a new product or service is their overall emotional response to it. The theory of reasoned action (TRA) suggests that behavior and intention are primarily influenced by social influence and attitudes (Fishbein & Ajzen, 1975; Park et al., 2014). Shiau and Chau (2016) further explain that online learning users' attitudes towards e-learning systems are based on their satisfaction level with a particular service.

Students' retention and positive attitudes toward online education have been challenged by the rapid development of blended learning in higher education (Liu et al., 2018). Students' intentions to study online were significantly influenced by their perception of usefulness, enjoyment, and satisfaction, which indicated a positive attitude (Guo et al., 2016). In order to employ learning strategies effectively (Maio et al., 2019), a strong attitude can guide behavior and create a positive attitude toward learning. As a result of relearning's positive impact on students' motivation and self-esteem (Nassoura, 2012), students have a positive attitude toward it. Agyei and Voogt (2011) has found that accessibility of technology affects the attitudes and competencies of both students and instructors and is positively related to technology use. The attitude of females and males toward MOOC and e-learning was similar (Rhema & Miliszewska, 2014). Based on the student's preferences for the online examination system, the students' attitude toward the online education system has been measured. Students' attitude toward examination is assumed to be positive when they have a positive attitude toward it. Thus, a hypothesis is proposed:

H4: Attitude has a significant impact on behavioral intentions.

2.5 Social influence

Social influence refers to how people perceive important others to believe they should use the new system (Venkatesh et al., 2003). An information system's intention to be used is influenced by how others perceive it (Zhou, 2011). When people get recommendations from people they care about, they are more likely to use that technology. As a result of receiving opinions from relatives, family, and colleagues, people are influenced to use technology to a certain extent (Riquelme & Rios, 2010). One's level of awareness of how others feel about using a new information system. It consists of social factors, images, and subjective norms, according to Venkatesh et al. (2003). The UTAUT model captures social influence as a combination of social factors and subjective norms. Numerous studies have demonstrated that social influence influences people's intentions to use technological innovations such as e-learning (Ali et al., 2018; Tarhini et al., 2017). This study assumes that lecturer, instructor, and colleague beliefs affect individuals' intention to use e-learning systems more in a mandatory environment than in a voluntary setup (Venkatesh & Davis, 2000).

In contrast, Oliveira et al. (2016) discovered that facilitating conditions did not significantly impact behavioral intention, which aligns with Lu (2014) finding that social influence strongly influences behavioral intention. Tarhini et al. (2017) study revealed that social influence continues to affect online learning users through their perceived usefulness. Thus, a hypothesis is proposed:

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

2.6 Behavioral intentions

Fishbein and Ajzen (1975) define *behavioral intention* as the subjective possibility of acting. According to Ajzen (1988), behavioral intention includes attitude towards behavior and subjective norms that impact behavior intention, which can predict and direct actual behavior. Therefore, behavioral intention can be used to predict and guide actual behavior. Agarwal and Prasad (1999) found that behavioral intention can be used as a substitute for mobile communication technology conduct in China, with age, gender, experience, and voluntariness acting as moderators that affect the relationship. Venkatesh and Morris (2000) reported that age and gender moderated the impact of effort expectancy, performance expectancy, and social influences on behavioral intention, whereas facilitating conditions moderated usage behavior. Venkatesh et al. (2003) explained that experience moderated the impact of effort expectancy on behavioral intention and that facilitating conditions moderated the impact of effort expectancy on behavioral intention.

Moreover, the voluntariness of use moderated the effects of social influence on behavioral intention. Davis (1989) and Venkatesh et al. (2003) considered behavioral intention a crucial component of the TAM model. Despite the extensive e-learning studies over the years, most studies have focused on behavioral intentions rather than actual use (Commer et al., 2018). Mohammadi (2015) found that behavioral intention was significantly influenced by examining various mobile learning contexts and user experiences using TAM, UTAUT, and IS models. Thakur and Srivastava (2014) also examined the intention of Indian customers to use mobile commerce. They reported that PU, PEOU, and social influence influenced customer behavior in e-learning and could affect behavioral intentions. Thus, behavioral intention can facilitate the adoption of new technologies. Thus, a hypothesis is proposed:

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

3. Research Methods and Materials

3.1 Research Framework

In the conceptual or designed framework, the researchers chose a particular research to conduct the research (Clark & Ivankova, 2016). Using a conceptual framework, you can illustrate how different factors or variables affect your research1. It consists of existing studies related to your topic and can be written or visual. It helps you organize your ideas and connect them clearly (Mohammadi, 2015). Therefore, this research used previous literature to summarize and identify relevant variables and presented them in Figure 1.

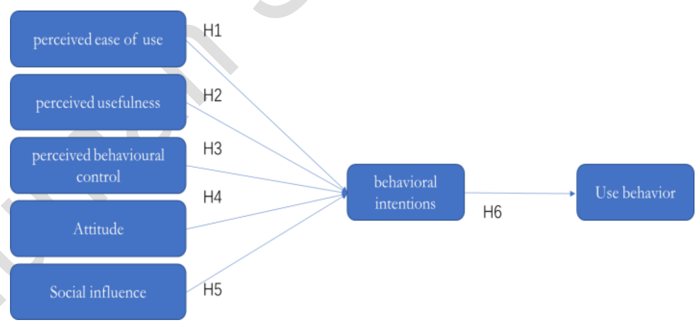

Figure 1: Conceptual Framework

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 intention.
H5: Social influence has a significant impact on behavioral intentions.
H6: Behavioral intentions have a significant impact on use behavior.

3.2 Research Methodology

During this study, the researcher collected and analyzed numerical data by posing questions to participants. The study included students from the top five vocational colleges in Jiangxi, China, and middle and top colleges. The questionnaire was administered both online and on paper. It consisted of three parts designed to gather and analyze data to identify the key factors influencing students' behavioral intentions. In the first step, the screening questions were used to identify respondents' characteristics to analyze all six hypotheses. A five-point Likert scale was also used to measure seven proposed variables, ranging from strong disagreement to strong agreement. Finally, Demographic questions, such as gender, age, and educational background, were also included. In the pilot testing stage, expert ratings of the index of item-objective congruence (IOC) and a pilot test were conducted with a broad range of respondents.

Cronbach's Alpha method was employed to evaluate both validity and reliability. The reliability of the questionnaire was gauged through a multi-stage process, beginning with an assessment involving the Index of Item-Objective Congruence (IOC) and a pilot test. The IOC assessment enlisted three experts to rate each item, all of which achieved scores of 0.6 or higher. Subsequently, a pilot test was administered to 50 participants, utilizing the Cronbach alpha coefficient to measure reliability. The findings indicated a robust internal consistency among all questionnaire items, with a reliability score of 0.7 or higher (Sarmento & Costa, 2016).

After the reliability test, the questionnaire was distributed to target respondents, which resulted in 500 accepted responses. The researcher analyzed the collected data through SPSS AMOS 27.0. Then, Confirmatory Factor Analysis (CFA) was used to test the convergence accuracy and validation. The model fit measurement was calculated with the overall test with given data to ensure the validity and reliability of the model. Lastly, the researcher applied the Structural Equation Model (SEM) to examine the effect of variables.

3.3 Population and Sample Size

As the population of this study, five vocational colleges in Jiangxi will be selected to represent this study. This study will investigate the relationship between each variable. Multistage sampling, including judgment or purposeful sampling, will be used to select the sample size. The sample size for Structural Equation Models suggested that at least 500 respondents (Kline, 2011) should participate in the study. The survey was given to 500 respondents. After the data screening process, 500 responses were used in this study.

3.4 Sampling Technique

The selection of five vocational colleges for the study employed nonprobability sampling techniques, which encompassed judgmental sampling. The sample size was determined using quota sampling, ensuring proportional representation. Data collection and survey distribution were facilitated through convenience sampling, utilizing the WenJuanXing platform. The distribution of required student numbers from each college, based on both the sample size and student proportion, is detailed in Table 1.

Table 1: Sample Units and Sample Size

College Name	Population Size	Proportional Sample Size
Jiangxi Tourism and Commerce Vocational College	11563	128
Jiangxi Vocational and Technical College of Communications	8550	94
Jiangxi Modern Polytechnic College	10720	118
Jiangxi Vocational Technical College of Industry & Trade	8542	94
Jiangxi Institute of Economic Ad ministrators	5891	66
Total	**45266**	**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 44.4% and female respondents account for 55.6% For the year of study, 122 sophomore students account for 26.5%, 330 junior students account for 66.1%, and 38 senior students account for 7.4%

Table 2: Demographic Profile

Demographic and General Data (N=500)		Frequency	Percentage
Gender	Male	222	44.4%
	Female	278	55.6%
Year of Study	Sophomore	122	24.4%
	Junior	330	66%
	Senior	48	9.6%

Source: Constructed by author

4.2 Confirmatory Factor Analysis (CFA)

Allen (2009) explain that measurement models and confirmatory factor analyses (CFA) identify variations and covariations among indicators. Brown (2006) further explains that CFA is a type of structural equation modeling that analyzes the relationship between observed and latent variables using a measurement model. According to Alkhadim et al. (2018), it is important to perform CFA for all latent variables in the structural model of the research. Perry et al. (2013) state that the objective of CFA is to determine the model's acceptability.

The findings revealed that all constructs exhibited robust internal consistency, with a reliability score equal to or exceeding 0.7 (Sarmento & Costa, 2016). This consistency is further underscored in Table 3, where Cronbach's Alpha values surpassed 0.7, signifying strong internal coherence. Additionally, composite reliability (CR) values surpassed 0.70, confirming the reliability of the measurements. The average extracted variance (AVE) values also exceeded 0.50, indicating substantial convergent validity. Moreover, all factor loading values surpassed 0.50, providing additional support for the validity of the factors. The significance of each item's factor loading, alongside acceptable values, affirms the convergent validity. Consequently, all estimates hold statistical significance

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)	Madhurima and Ewuuk (2014)	4	0.828	0.686–0.83	0.845	0.578
Perceived usefulness (PU)	Buabeng-Andoh (2018)	4	0.879	0.767–0.81	0.866	0.617
Perceived behavioral control (PBC)	Moorthy et al. (2017)	4	0.865	0.752–0.82	0.864	0.614
Attitude (AT)	Oertzen and Schröder (2019)	4	0.821	0.647–0.869	0.827	0.548
Social influence (SI)	Thakur and Srivastava (2014)	5	0.886	0.712–0.828	0.877	0.589
Behavioral intentions (BI)	Moorthy et al. (2017)	4	0.803	0.573–0.794	0.824	0.544
Use Behavior (UB)	Kim and Kwahk (2007)	4	0.841	0.721–0.809	0.849	0.585

In Table 4, it can be observed that the square root of the average variance extracted (AVE) demonstrates that all correlations are higher than the respective correlation values for each variable. Moreover, indicators such as GFI, AGFI, NFI, CFI, TLI, and RMSEA are utilized for model fit evaluation in the 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)	3.746
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.859
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.828
NFI	≥ 0.80 (Wu & Wang, 2006)	0.834
CFI	≥ 0.80 (Bentler, 1990)	0.872
TLI	≥ 0.80 (Sharma et al., 2005)	0.854
RMSEA	< 0.08 (Pedroso et al., 2016)	0.074
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

As shown in Table 5, this study's convergent validity and discriminant validity are greater than acceptable values, so these validity and discriminant validity are confirmed.

Table 5: Discriminant Validity

	PEOU	PU	PBC	AT	SI	BI	UB
PEOU	0.760						
PU	0.259	0.785					
PBC	0.300	0.277	0.784				
AT	0.181	0.256	0.201	0.740			
SI	0.240	0.241	0.227	0.151	0.767		
BI	0.412	0.478	0.374	0.448	0.439	0.765	
UB	0.443	0.468	0.433	0.369	0.243	0.540	0.738

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) is used to validate causal relationships among variables in a proposed model and to consider measurement inaccuracies in structure coefficients, according to Hair et al. (2010). Structural Equation Model (SEM) goodness of fit indices are presented in Table 6. below. The model fit measurement should not be over 3 for the 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 = 3.410, GFI = 0.854, AGFI = 0.827, NFI = 0.843, CFI = 0.883, TLI = 0.871, and RMSEA = 0.069., 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)	3.410
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.871
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.827
NFI	≥ 0.80 (Wu & Wang, 2006)	0.883
CFI	≥ 0.80 (Bentler, 1990)	0.843
TLI	≥ 0.80 (Sharma et al., 2005)	0.854
RMSEA	< 0.08 (Pedroso et al., 2016)	0.069
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

A regression coefficient or standardized path coefficient can be used to measure the correlation between independent and dependent variables. Among the six hypotheses proposed in Table 7, five were supported. Behavioral intention (BI) strongly influenced Use Behavior (UB). The influence of Behavioral intention (BI) was significantly influenced by Perceived ease of use (PEOU), Perceived behavioral control (PBC), and Perceived usefulness (PU), respectively.

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-Value	Result
H1: PEOU →BI	0.320	6.530***	Supported
H2: PU→BI	0.368	7.462***	Supported
H3: PBC→BI	0.283	5.910***	Supported
H4: AT→BI	0.260	5.271***	Supported
H5: SI→BI	0.086	1.891	Not Supported
H6: BI→UB	0.569	9.555***	Supported

Note: *** p<0.001, ** p<0.01, * p<0.05
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), revealing the standard coefficient value of 0.320 in the structural pathway. Fan et al. (2021) confirmed that Perceived ease of use (PEOU) can enhance users' Behavioral intention (BI). However, the appropriate level of Perceived ease of use (PEOU) must be deployed to drive students to learn easily and efficiently at the college. In terms of **H2,** the analysis outcome supported the hypothesis of the significant influence of Perceived usefulness (PU) on students' Behavioral intention, representing the standard coefficient value of 0.368 Per the study of Fan et al. (2021), the discussion implied that Perceived usefulness (PU) among individuals can drive students' behavior to generate knowledge and ideas during learning time. **H3** has postulated the significant impact of Perceived behavioral control (PBC) on Behavioral intention (BI), resulting in the standard coefficient value of 0.283.

Additionally, perceived behavioral control is regarded as a crucial factor in predicting and understanding behavior, as it is believed to influence an individual's motivation to act, which means it encourages students to perform to the best of their ability. The result supported the previous literature that Perceived behavioral control (PBC) showed the highest significant impact on Behavioral intention (BI) in this study. Another significant factor impacting Behavioral intention (BI) is attitude (AT), with a standardized path coefficient of 0.260 and a t-value of 5.271 **(H4).** Attitude can influence the degree of online learning system usefulness perceived by students Al-Omairi and Al Balushi (2015), Lin (2007), and Perkowitz and Etzioni (1999). The strongest impact on Behavioral intention (BI) is social influence (SI). The path relationship of social influence (SI) and Behavioral intention (BI) has a standardized path coefficient of 0.086 in **H5.** This supports the previous studies of Fan et al. (2021). Social influence (SI) in conformity, compliance, or obedience is another vital attribute of the online learning system's usefulness.

Finally, Behavioral intention (BI) on Use Behavior (UB) demonstrated a value of 0.569 on the standard coefficient, reinforcing the significant impact of H6. To support this statement, the Behavioral intention (BI) support significantly influences the Use Behavior (UB) at study as the student is comfortable and useful for information collection in the efficient rhythm to complete the task. (Prieto & Pérez-Santana, 2014).

5. Conclusion and Recommendation

5.1 Conclusion and Discussion

This study's objective was to comprehensively analyze the factors influencing vocational Associate students' behavioral intention and use behavior towards Online Learning Systems in Jiangxi, China. The researcher proposed six hypotheses to correspond with the research questions, which aimed to examine whether Perceived ease of use (PEOU), Perceived usefulness (PU), Perceived behavioral control (PBC), Attitude (AT), and social influence (SI) have a direct or indirect impact on behavioral intention to use online learning system. The study targeted students from five vocational higher education colleges in Jiangxi, China, who had experience studying with online learning systems. The sampling procedures involved multi-stage sampling, including judgmental sampling to select the colleges in Jiangxi, stratified random sampling to allocate the sample size proportionately to each college, and convenience sampling for questionnaire distribution. The data was collected quantitatively through a questionnaire containing screening questions, measurement of all variables using a five-point Likert scale, and demographic questions of respondents. The reliability and consistency of each measurement item were ensured by conducting an Item-Objective Congruence (IOC) and pilot test. Confirmatory Factor Analysis (CFA) was used to measure and test the validity and reliability of the research conceptual model. The composite reliability, Cronbach's alpha reliability, factor loading, average variance extracted analysis, and discriminant validity measured the results. Structural Equation Modelling (SEM) was employed to analyze and discuss the factors influencing vocational students' behavioral intention and use of online learning systems. The study concluded with a description of the findings.

Firstly, the study found that social influence (SI) was the strongest predictor of behavioral intention among students and that behavioral intention significantly influences Use Behavior (UB). This relationship is consistent with previous literature from Aaker and Maheswaran (1997). Therefore, expanding the social aspect and advantages of the online learning system is important to motivate behavioral intention among students.

Secondly, the study found that Perceived usefulness (PU) significantly impacts behavioral intention. This is because users' evaluation of the utility of new IT, such as performance based on a target, affects behavioral intention significantly. Additionally, Perceived ease of use (PEOU) was also found to be an important factor that impacts behavioral intention.

Lastly, the study confirmed that Behavioral intention significantly influences Use Behavior (UB). This is particularly true when there is a persistent 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 study conducted by the researcher in five higher Associate vocational colleges in Jiangxi, China, identified key factors, including Perceived ease of use (PEOU), Perceived usefulness (PU), Perceived behavioral control (PBC), Attitude (AT), and social influence (SI), which impact behavioral intention (BI) and Use Behavior (UB) towards online learning systems. Trust was found insignificant and, therefore, not a key factor. The study found that social influence (SI) was the strongest predictor of behavioral intention to use online learning systems, indicating that it is important to emphasize the influence of behavioral intention on the use behavior of the system. This implies that students are likely to adopt online learning systems if they perceive them as useful tools to enhance their vocational performance. To ensure that the attributes of PEOU, PU, PBC, and AT are available when using online learning systems, developers of course systems, teachers, and top management of higher Associate vocational colleges should ensure that the features provided by online learning systems are responsive, flexible, accurate, and relevant to their studies. Quality technical assistance should also be provided, and sufficient training should be conducted to improve practitioners' practical ability, helping learners learn online courses more effectively and improving their willingness to accept online learning systems. Once the quality features are ensured, the usefulness, operation procedures, and other facilities supported by the system should be promoted to students through training and media communications to increase 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 bachelor’s degree 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.

References

Aaker, J. L., & Maheswaran, D. (1997). The effect of cultural orientation on persuasion. *Journal of Consumer Research, 24*(3), 315-328. https://doi.org/10.1086/209513

Agarwal, R., & Prasad, J. (1999). Are Individual Differences Germane to the Acceptance of New Information Technologies? *Decision Sciences, 30,* 361-391. http://dx.doi.org/10.1111/j.1540-5915.1999.tb01614.x

Agyei, D. D., & Voogt, J. M. (2011). Exploring the potential of the will, skill, tool model in Ghana: Predicting prospective and practicing teachers' use of technology. *Computer & Education, 56*(1), 91-100. https://doi.org/10.1016/j.compedu.2010.08.017

Ajzen, I. (1988). *Attitudes, Personality, and Behavior* (1st ed.). Dorsey.

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50*(2), 179-211. https://doi.org/10.1016/0749-5978(91)90020-t

Ajzen, I. (2002). Perceived Behavioral Control, Self-Efficacy, Locus of Control, and the Theory of Planned Behavior. *Journal of Applied Social Psychology, 32,* 665-683. http://dx.doi.org/10.1111/j.1559-1816.2002.tb00236.x

Ajzen, I. (2012). The Theory of Planned Behaviour, In P. A. M. Lange, A. W. Kruglanski & E. T. Higgins (Eds.), *Handbook of Theories of Social Psychology* (pp. 438-459). Sage. https://doi.org/10.4135/9781446249215.n22

Akturan, U., & Tezcan, N. (2012). Mobile Banking Adoption of the Youth Market: Perceptions and Intentions. *Marketing Intelligence & Planning, 30,* 444-459. https://doi.org/10.1108/02634501211231928

Alexandersson, M., & Limberg, L. (2012). Changing Conditions for Information Use and Learning in Swedish Schools: A Synthesis of Research. *HumanIT, 11*(2), 131-154.

Ali, S., Ahmad Ganai, B., Kamili, A. N., & Ali Bhat, A. (2018). Pathogenesis-related proteins and peptides as promising tools for engineering plants with multiple stress tolerance. *Microbiological Research, 212,* 29-37. https://doi.org/10.1016/j.micres.2018.04.008

Alkhadim, M., Gidado, K., & Painting, N. (2018). Perceived Crowd Safety in Large Space Buildings: The Confirmatory Factor Analysis of Perceived Risk Variables. *Journal of Engineering, Project, and Production Management, 8*(1), 22-39. https://doi.org/10.32738/jeppm.201801.0004

Allen, R. C. (2009). *The British Industrial Revolution in Global Perspective* (1st ed.). Cambridge University Press.

Al-Mamary, Y. H., & Shamsuddin, A. (2015). Adoption of Management Information Systems in Context of Yemeni Organizations: A Structural Equation Modeling Approach. *Journal of Digital Information Management, 13*(6), 429-444.

Al-Omairi, T., & Al Balushi, H. (2015). The Influence of paying attention in classroom on students' academic achievement in terms of their comprehension and recall ability. *Proceedings of INTCESS15- 2nd International Conference on Education and Social Sciences*, 684-693.

Amin, M. H. A., Rahaman, M. S., & Azad, M. O. K. (2008). Effect of initial moisture content and different storage container on the quality of grass pea (Lathyrus sativa) seed. *Int. J. Sust. Crop Prod., 3*(3), 18-24.

Anckar, B., Walden, P., & Jelassi, T. (2002). Creating customer value in online grocery shopping. *International Journal of Retail & Distribution Management, 30*(4), 211-220.

Armitage, C. J., & Conner, M. (2001). Efficacy of the Theory of Planned Behaviour: A Meta Analytic Review. *British Journal of Social Psychology, 40*(4), 471-499. https://doi.org/10.1348/014466601164939

Arpaci, I. (2016). Understanding and predicting students' intention to use mobile cloud storage services. *Computers in Human Behavior. 58*, 150-157. https://doi.org/10.1016/j.chb.2015.12.067

Awang, Z. (2012). *A Handbook on SEM Structural Equation Modelling: SEM Using AMOS Graphic* (5th ed.). Universiti Teknologi Mara Kelantan.

Behrend, T., Sharek, D., Meade, A., & Wiebe, E. (2011). The viability of crowdsourcing for survey research. *Behavior Research Methods, 43*(3), 800-813.

Bentler, P. M. (1990). Comparative fit indexes in structural models. *Psychological Bulletin, 107*(2), 238-246. https://doi.org/10.1037/0033-2909.107.2.238

Bidin, S. J., & Jomaa, N. (2019). Variations in the Citation Use and Perceptions in Writing the Literature Review by EFL Postgraduates. *Eurasian Journal of Applied Linguistics, 5*(3), 441-460. https://doi.org/10.32601/ejal.651398

Bolduc, H., & Kinnally, W. (2018). Examining the Impact of Social Identification with Music-on-Music Streaming Behavior. *Journal of Radio & Audio Media, 25*(1), 42-61. https://doi.org/10.1080/19376529.2017.1362893

Brown, T. A. (2006). *Confirmatory Factor Analysis for Applied Research* (1st ed.). The Guilford Press.

Buabeng-Andoh, C. (2018). Predicting students' intention to adopt mobile learning: A combination of theory of reasoned action and technology acceptance model. *Journal of Research in Innovative Teaching & Learning, 11*(2), 178-191. https://doi.org/10.1108/JRIT/03-2017-000

Clark, V. L. P., & Ivankova, N. V. (2016). *Mixed Methods Research: A Guide to the Field* (1st ed.). SAGE Publications.

Commer, P., Sci, S., Sair, S. A., & Danish, R. (2018). Effect of Performance Expectancy and Effort Expectancy on the Mobile Commerce Adoption Intention through Personal Innovativeness among Pakistani Consumers. *Pakistan Journal of Commerce and Social Science, 12*, 501-520.

Crabbe, M., Standing, C., Standing, S., & Karjaluoto, H. (2009). An adoption model for mobile banking in Ghana. *IJMC, 7*(5), 515-543. https://doi.org/10.1504/ijmc.2009.024391

Davis, F. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Quarterly, 13*, 319-340. https://doi.org/10.2307/249008

Fan, X., Duangekanong, S., & Xu, M. (2021). Factors Affecting College Students' Intention to Use English U-learning in Sichuan, China. *AU-GSB E-JOURNAL, 14*(2), 118-129. https://doi.org/10.14456/augsbejr.2021.20

Fishbein, M., & Ajzen, I. (1975). *Belief, Attitude, Intention, and Behavior: An Introduction to Theory and Research* (1st ed.). Addison-Wesley.

Gerhardt, T., & Mackenzie, L. (2018). The Challenges and Opportunities of ICT in WIL: A case study among priests exploring the correlation and trajectory between effective WIL and ICT Pervasiveness. *Journal of Higher Education, 8*(4), 408-421. https://doi.org/10.1108/heswbl-07-2017-0045

Guo, F., Yu, J., Jung, H. J., Abruzzi, K. C., Luo, W., Griffith, L. C., & Rosbash, M. (2016). Circadian neuron feedback controls the Drosophila sleep--activity profile. *Nature 536*(7616), 292-297. https://doi.org/10.1038/nature19097

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). *Multivariate Data Analysis* (7th ed.). Pearson.

Ho, Y.-S. (2012). The top-cited research works in the Science Citation Index Expanded. *Scientometrics, 94*, 1297-1312. https://doi.org/10.1007/s11192-012-0837-z

Huang, Y.-H. (2016). Beyond Safety Outcomes: An Investigation of the Impact of Safety Climate on Job Satisfaction, Employee Engagement and Turnover Using Social Exchange Theory as the Theoretical Framework. *Applied Ergonomics, 55*, 248-257. https://doi.org/10.1016/j.apergo.2015.10.007

John, H. (2013). *Men in Black* (1st ed.). Reaktion Books

Khalifa, M., & Shen, K. (2008). Explaining the adoption of transactional B2C mobile commerce. *J. Enterprise Inf. Management, 1*(2), 110-124.

Kim, H.-W., & Kwahk, K.-Y. (2007). Comparing the Usage Behavior and the Continuance Intention of Mobile Internet Services. *Management of eBusiness, 2007. WCMeB 2007. Eighth World*, 1-15. https://doi.org/10.1109/wcmeb.2007.98

Kline, R. B. (2011). *Principles and Practice of Structural Equation Modeling* (1st ed.). Guilford Press.

Lin, H.-F. (2007). Knowledge Sharing and Firm Innovation Capability: An Empirical Study. *International Journal of Manpower, 28*, 315-332. https://doi.org/10.1108/0143772071075527

Linnenbrink, E. A. (2007). The role of affect in student learning: A multi-dimensional approach to considering the interaction of affect, motivation, and engagement. In P. A. Schutz & R. Pekrun (Eds.), *Emotion in education* (pp. 107-124). Elsevier Academic Press. https://doi.org/10.1016/B978-012372545-5/50008-3

Littlejohn, A., Hood, N., Milligan, C., & Mustain, P. (2015). Learning in MOOCs: Motivations and self-regulated learning in MOOCs. *The Internet and Higher Education, 29*(4), 40-48. https://doi.org/10.1016/j.iheduc.2015.12.003

Liu, C., & Forsythe, S. (2010). Sustaining Online Shopping: Moderating Role of Online Shopping Motives. *Journal of Internet Commerce, 9*(2), 83-103. https://doi.org/10.1080/15332861.2010.503848

Liu, W., Mumford, E., & Taylor, B. (2018). The Relationship Between Parents' Intimate Partner Victimization and Youths' Adolescent Relationship Abuse. *Journal of Youth and Adolescence, 47*(2), 321-333. https://doi.org/10.1007/s10964-017-0733-1

Liyanagunawardena, T., Williams, S., & Adams, A. (2013). The impact and reach of MOOCs: a developing countries' perspective. *eLearning Papers, 1*(33), 1-8.

Lu, J. (2014). Are Personal Innovativeness and Social Influence Critical to Continue with Mobile Commerce? *Internet Research, 24*(2), 134-159. https://doi.org/10.1108/intr-05-2012-0100

Madhurima, D., & Ewuuk, L.-D. (2014). An empirical examination of customers' adoption of m-banking in India. *Marketing Intelligence & Planning, 32*(4), 475-494.

Maio, G., Haddock, G., & Verplanken, B. (2019). *The psychology of attitudes & attitude change* (1st ed.). Sage Publications.

Mallat, N., Rossi, M., Tuunainen, V., & Öörni, A. (2009). The Impact of use Context on Mobile Services Acceptance: The Case of Mobile Ticketing. *Information & Management, 46*(3), 190-195. https://doi.org/10.1016/j.im.2008.11.008

Mathwick, C., Malhotra, N., & Rigdon, E. (2001). Experiential Value: Conceptualization, Measurement and Application in the Catalog and Internet Shopping Environment. *Journal of Retailing, 77*, 39-56. https://doi.org/10.1016/S0022-4359(00)00045-2

Mohammadi, H. (2015). A Study of Mobile Banking Usage in Iran. *International Journal of Bank Marketing, 33*, 733-759. https://doi.org/10.1108/IJBM-08-2014-0114

Moorthy, M., Ling, C., Fatt, Y., Yee, C., Yin, E., Yee, K., & Wei, L. (2017). Barriers of Mobile Commerce Adoption Intention: Perceptions of Generation X in Malaysia. *Journal of theoretical and applied electronic commerce research, 12*(2), 37-53. https://doi.org/10.4067/s0718-18762017000200004

Nassoura, A. B. (2012). Students' acceptance of mobile learning for higher education in Saudi Arabia. *American Academic & Scholarly Research Journal, 4*(2), 1-10.

Nysveen, H., Pedersen, P., & Thorbjørnsen, H. (2005). Intentions to Use Model Services: Antecedents and Cross-Service Comparisons. *Journal of the Academy of Marketing Science, 33*(3), 330-346. https://doi.org/10.1177/0092070305276149

Oertzen, A.-S., & Schröder, G.-O. (2019). Achieving continued usage in online banking: A post-adoption study. *International Journal of Bank Marketing, 37*(6), 1394-1418. https://doi.org/10.1108/ijbm-09-2018-0239

Oliveira, H. C., Garcia, R., Almeida, V. V. S., Oliveira, A. C., Pires, A. J. V., Nascimento, C. S., Veloso, C. M., Silva, R. R., & Oliveira, U. L. C. (2016). Feeding behavior of lambs fed castor meal. Semin. *Cienc. Agrar., 37*(3), 1451-1460. https://doi.org/10.5433/1679-0359.2016v37n3p1451

Park, Y. K., Song, J. H., Yoon, S. W., & Kim, J. (2014). Learning Organization and Innovative Behavior: The Mediating Effect of Work Engagement. *European Journal of Training and Development, 38*, 75-94. https://doi.org/10.1108/EJTD-04-2013-0040

Pedroso, R., Zanetello, L., Guimaraes, L., Pettenon, M., Goncalves, V., Scherer, J., Kessler, F., & Pechansky, F. (2016). Confirmatory factor analysis (CFA) of the crack use relapse scale (CURS). *Archives of Clinical Psychiatry, 43*(3), 37-40. https://doi.org/10.1590/0101-60830000000081

Perkowitz, M., & Etzioni, O. (1999). Towards adaptive Web sites: Conceptual framework and case study. *Artificial Intelligence 118*(1-2), 245-275.

Perry, A., Orly, R., Peled-Avron, L., & Shamay-Tsoory, S. (2013). Don't stand so close to me: A behavioral and ERP study of preferred interpersonal distance. *NeuroImage, 83*(1), 761-769. https://doi.org/10.1016/j.neuroimage.2013.07.042

Pipitwanichakarn, T., & Wongtada, N. (2020). The role online review on mobile commerce adoption: an inclusive growth context. *Journal of Asia Business Studies, 14*(5), 759-778. https://doi.org/10.1108/jabs-02-2019-0060

Prieto, I., & Pérez-Santana, M. (2014). Managing innovative work behavior: *The role of human resource practices. Personnel Review, 43*(2), 1-10.

Rhema, A., & Miliszewska, I. (2014). Analysis of Student Attitudes towards E-learning: The Case of Engineering Students in Libya. *Issues in Informing Science and Information Technology, 11*, 169-190. https://doi.org/10.28945/1987

Riquelme, H. E., & Rios, R. E. (2010). The Moderating Effect of Gender in the Adoption of Mobile Banking. *The International Journal of Bank Marketing, 28*, 328-341. http://dx.doi.org/10.1108/02652321011064872

Rogers, E. M. (1962). *Diffusion of Innovations* (1st ed.). Free Press.

Samuel, A., Susan, M., & Biniecki, Y. (2017). Using concept mapping as a tool for conducting research: An analysis of three approaches. *Cogent Social Sciences, 3*(1), 1404753. https://doi.org/10.1080/23311886.2017.1404753

Sarmento, R., & Costa, V. (2016). *Comparative Approaches to Using R and Python for Statistical Data Analysis* (1st ed.). IGI Global Press.

Sharma, S., Pradhan, K., Satya, S., & Vasudevan, P. (2005). Potentiality of earthworms for waste management and in other uses- a review. *The J. Am. Sci.*, *1*(1), 4-16

Shiau, W. L., & Chau, P. Y. (2016). Understanding behavioral intention to use a cloud computing classroom: A multiple model comparison approach. *Information & Management, 53*, 355-365. https://doi.org/10.1016/j.im.2015.10.004

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

Stark, J. S., & Lattuca, L. R. (1997). *Shaping the College Curriculum: Academic Plans in Action* (1st ed.). Evaluative.

Tarhini, A., Masa'deh, R., Al-Busaidi, K. A., Bany Mohammed, A., & Maqableh, M. (2017). Factors influencing students' adoption of e-learning: A structural equation modeling approach. *Journal of International Education in Business. 10*(2), 164-182. https://doi.org/10.1108/jieb-09-2016-0032

Taylor, D. G., & Strutton, D. (2010). Has e-marketing come of age? Modeling historical influences on post-adoption era Internet consumer behaviors. *Journal of Business Research, 63*(9-10), 950-956. https://doi.org/10.1016/j.jbusres.2009.01.018

Tenorio, M. L., Dekker, M., & Verkerk, R. (2017). Evaluating the effect of storage conditions on the shelf life of cape gooseberry. *LWT, 80,* 523-530. https://doi.org/10.1016/j.lwt.2017.03.027

Thakur, R., & Srivastava, M. (2014). Adoption readiness, personal innovativeness, perceived risk, and usage intention across customer groups for mobile payment services in India. *Internet Research: Electronic Networking Applications and Policy, 24*(3), 369-392. https://doi.org/10.1108/intr-12-2012-0244

Van Manen, M. (1997). *Researching Lived Experience: Human Science for an Action Sensitive Pedagogy* (2nd ed.). Althouse Press.

Venkatesh, V., & Davis, F. D. (2000). A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies. *Management Science, 46,* 186-204. https://doi.org/10.1287/mnsc.46.2.186.11926

Venkatesh, V., & Morris, M. G. (2000). Why Don't Men Ever Stop to Ask for Directions? Gender, Social Influence, and Their Role in Technology Acceptance and Usage Behavior. *MIS Quarterly, 24,* 115-139. https://doi.org/10.2307/3250981

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User Acceptance of Information Technology: Towards a Unified View. *MIS Quarterly, 27,* 425-478.

Wang, Z., Guo, D., & Wang, X. (2016). Determinants of Residents' E-Waste Recycling Behaviour Intentions: Evidence from China. *Journal of Cleaner Production, 137,* 850-860. https://doi.org/10.1016/j.jclepro.2016.07.155

Wu, J. H., & Wang, Y. M. (2006). Measuring KMS Success: A Respecification of the DeLone and McLean's Model. *Journal of Information & Management, 43*(6), 728-739. http://dx.doi.org/10.1016/j.im.2006.05.002

Zeithaml, V. A., Parasuraman, A., & Malhotra, A. (2002). Service Quality Delivery through Web Sites: A Critical Review of Extant Knowledge. *Journal of the Academy of Marketing Science, 30,* 362-375. https://doi.org/10.1177/009207002236911

Zhou, T. (2011). Understanding mobile internet continuance usage from the perspectives of UTAUT and flow. *Information Development, 27*(3), 207-218. https://doi.org/10.1177/0266666911414596