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Influential Factors on the Utilization of E-Learning Systems among Second-Year Arts Major Students in Higher Vocational Colleges in Henan, China

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Abstract

Purpose: The objective of this study is to explore the factors impacting the use behavior of e-learning systems among second year of art majors in higher vocational colleges in Henan, China. The research framework introduces subjective norm, effort expectancy, internet experience, e-learning motivation, perceived usefulness, behavioral intention, and use behavior. **Research design, data, and methodology:** The researcher employed a quantitative research method and distributed questionnaires to 500 sophomore students in arts majors at a public higher vocational college in Henan province. The initial content validity and reliability assessment was carried out using Item Objective Consistency and Cronbach's Alpha. After the data was collected, Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM) were employed to analyze the data, validate the model fit, and confirm the causal relationships between variables, testing the hypotheses for their reliability and validity. **Results:** The results of the study suggest that the use behavior in the e-learning system among second-year students majoring in arts at vocational colleges is significantly impacted by subjective norm, effort expectancy, internet experience, e-learning motivation, perceived usefulness, and behavioral intention. **Conclusions:** It is recommended to designing and promoting e-learning systems to enhance successful adoption and effective utilization.

Keywords : Subjective Norm , Effort Expectancy, Perceived Usefulness, Behavioral Intention, Use Behavior

JEL Classification Code: E44, F31, F37, G15

1. Introduction

With the widespread popularity of the Internet and the rapid development of technology, global online learning is experiencing a continuous growth trend. More students and professionals are acquiring new knowledge and skills through online learning. According to Palvia et al. (2018), various forms of online education are steadily growing worldwide. Behind this trend is the continuous integration of new technologies and the extensive use of the Internet globally, further driving the increased demand for regular workforce training for the digital economy.

E-learning has evolved into a revolutionary learning method (Cappel & Hayen, 2004). Driven by technological innovation, training, teaching, and learning through the Internet have become possible, referred to as Web-based instruction in education and training (Lee, 2001). As an alternative to traditional face-to-face, teacher-guided education, e-learning has received considerable attention (Douglas & Van Der Vyver, 2004).

For quite a long time, China's education model has remained largely unchanged, particularly in higher education, where the teaching approach has consistently adhered to a relatively traditional format: professors lecturing, taking notes, and completing assigned homework. Face-to-face teaching and communication have always been regarded as integral components of knowledge transmission. However, innovative education delivery systems, such as interactive

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and reflective learning methods (Haverila & Barkhi, 2009), have challenged traditional education models. The widespread application of electronic technology has shown numerous new features that can be employed to make teaching more engaging (Keller & Suzuki, 2004). Throughout this series of transformations, it is widely believed that new technologies have significantly impacted teaching. Everyone must comprehend, acquire, and proficiently grasp fundamental technological knowledge, employing it to attain educational goals.

E-learning refers to education and training provided through Information and Communication Technology (ICT), specifically focusing on supporting individual learning or achieving organizational performance objectives (Clark & Mayer, 2023; Sun et al., 2008). In the Internet era, e-learning is viewed as a means for individuals and organizations to keep pace with the evolving global economic changes. E-learning is characterized by its cost-effectiveness, flexibility, and ease of delivery, overcoming time and distance limitations (Carey & Blatnik, 2005), making it an attractive choice for developing countries. Islam and Selim (2006) point out that in recent years, Information and Communication Technology has rapidly expanded in some developing countries, providing an opportunity to consider using ICT to promote digital education. This brings numerous benefits to students, including increased learning opportunities, lifelong learning possibilities, and convenient time and location (Pierre, 1998).

During the widespread outbreak of the 2019 coronavirus, many countries experienced significant impacts across various sectors, including education, tourism, social life, and the economy (Baldwin & Tomiura, 2020; Nicola et al., 2020). Due to the influence of the COVID-19 pandemic, e-learning has emerged as a crucial method in education. This worldwide health emergency prompted schools and educational institutions to take urgent measures, shifting towards online education to ensure uninterrupted learning for students. E-learning, facilitated through various digital platforms and tools, offers students a learning experience distinct from traditional classrooms. Students can access course content, participate in remote learning activities, and engage in online interactions and discussions with teachers and classmates through the Internet.

Considering the increasing popularity of e-learning systems, researchers, based on the background above, chose second-year students majoring in arts at Henan Vocational Institute of Arts as the target group for their study. They analyze various factors influencing these students' behavior in using e-learning systems.

Because of its ability to meet individual learning needs, e-learning has gained widespread recognition. E-learning has successfully prioritized learners' unique requirements over the demands of educational institutions or teachers, effectively driving knowledge transfer in the digital age (Huang & Chiu, 2015).

2. Literature Review

2.1 Subjective Norm

According to Yazdanmehr and Wang (2016), subjective norms refer to an individual's understanding of how their behavior is influenced within a specific context by significant individuals in their life, such as family members, friends, and supervisors. Ajzen (1991) considered subjective norms "normative beliefs," centering on the probability of obtaining approval or disapproval from important individuals or groups while participating in a particular behavior. Ajzen (1991) and O'Neal (2007) stress that subjective norms are connected to individuals' perceptions of the influence and expectations affecting them, determining whether they are motivated or deterred from participating in specific behaviors. Prior research has highlighted the significance of the connection between subjective norms and intentions to engage in certain behaviors. In the Theory of Reasoned Action (TRA) proposed by Fishbein and Ajzen (1975), as well as in the Theory of Planned Behavior (TPB) developed by Ajzen (1991), when assessing behavioral intentions, social influence is regarded as an integral component of subjective norms. According to Fishbein and Ajzen (1975), the subjective norms of individuals are influenced by their perceptions, specifically whether they believe they should or should not engage in a particular behavior. For instance, students may perceive that teachers hope them to make use of e-learning systems. If students have a strong motivation to adhere to the teacher's expectations, this will positively influence their subjective norms. Subjective norms are an external motivator in how university students self-regulate their engagement with e-learning (Park, 2009).

Consequently, the research covers subjective norms related to using e-learning systems. Previous studies have provided abundant theoretical and empirical support suggesting that the importance of technology use is directly or indirectly influenced by subjective norms, particularly through the perceived usefulness in the workplace (Hsu & Lu, 2004; Taylor & Todd, 1995; Venkatesh & Davis, 2000). Due to its significant positive impact on behavior, the sharing intention was discovered to depend on the subjective norm (Chow & Chan, 2008). Therefore, the above findings allow hypotheses to be established:

H1: Subjective norm has a significant impact on perceived usefulness.

H5: Subjective norm has a significant impact on behavioral intention.

2.2 Effort Expectancy

Sair and Danish (2018) defined effort expectancy as an individual's perception of the difficulty in adopting technology and the simplicity of its usage. According to Yadav et al. (2016), effort expectancy indicates an individual's assurance in their capability to utilize technology without requiring extra effort. The study by Venkatesh et al. (2012) stated that effort expectancy is linked to how users perceive the simplicity of technology usage. Zhou et al. (2010) highlighted the direct correlation between effort expectancy and behavioral intention using the Unified Theory of Acceptance and Use of Technology (UTAUT) framework. Chaouali et al. (2016) pointed out the positive impact of perceived effort expectancy on internet users' performance expectations when adopting technology. In the study of Onaolapo and Oyewole (2018), they suggested that the use of smartphones for e-learning by graduate students is directly affected by their effort expectancy. Al-Gahtani et al. (2007) and Lin and Anol (2008) research substantiated a significant association between effort expectation and the intention to engage in specific behaviors. Previous research conducted by Sharma et al. (2016) and Zuiderwijk et al. (2015) consistently suggests that effort expectation positively impacts the willingness to utilize a system.

Additionally, the research conducted by Tarhini et al. (2017a) and Mtebe and Raisamo (2014) has been recognized as a crucial determinant affecting the tendency to use e-learning systems. Chang (2013) demonstrates a positive correlation between the increase in effort expectancy and customers' intentions in their behavior. Therefore, the following hypothesis is proposed:
H2: Effort expectancy has a significant impact on behavior intention.

2.3 Internet Experience

The characteristics of internet experience refer to the proficiency or capability that consumers acquire through interactions across various websites and using different value-added services provided on those websites (Nysveen & Pedersen, 2004). According to Kim (2010), the features of the Internet experience involve a comprehensive and all-encompassing understanding cultivated by individuals through exploring websites and actively engaging with various value-added Internet services. The internet experience improves the skilled use of website applications, causing experienced internet users to develop more positive opinions regarding using specific websites (Chen & Macredie, 2005). Individuals' utilization and internet experience significantly correlate with their acceptance of technology (Ali et al., 2015). Liao and Cheung (2001) suggest that Internet Experience is the most crucial factor influencing users' inclination to participate in online shopping. It significantly contributes to the use behavior of online shopping systems. Additional research by Anandarajan et al. (2000) emphasizes the Internet Experience's significance in technology-related research. Prior research has recognized the importance of internet experience as a crucial factor in adopting technology, and it should be regarded as one of the main determinants (Abbad et al., 2011; Ali et al., 2015; Speier & Venkatesh, 2002). Hence, the following hypothesis is presented:
H3: Internet experience has a significant impact on behavior intention.

2.4 E-learning Motivation

Vallerand et al. (1992) defined extrinsic motivation as the pursuit of goals to achieve specific outcomes rather than being driven by the inherent value of the activity itself. In contrast, Vallerand et al. (1992) defined intrinsic motivation as the experience of joy and satisfaction derived from participating in an activity. According to earlier research (Coovert & Goldstein, 1980; Davis et al., 1992; Moon & Kim, 2001;), the intention to utilize information technology systems is significantly affected by both extrinsic and intrinsic motivations. Motivation is characterized as the extent of determination and driving force exhibited by individuals as they strive to achieve their goals (Johns, 1996). According to Law et al. (2010), learning motivation can be defined by the level of persistent effort that students dedicate to pursuing the learning process. Learning motivation reflects the desire and eagerness of students to actively engage in training activities when pursuing the intention of acquiring knowledge from experience (Harandi, 2015). E-learning motivation is defined as the tendency of students to perceive e-learning systems as valuable and easy to operate, along with their active motivation to pursue and obtain the academic advantages provided by these systems (Paola Torres Maldonado et al., 2011). The e-learning motivation comprises components within the motivation, performance expectancy, and effort expectancy. These components directly influence the intention to use (Davis et al., 1992; Moon & Kim, 2001). The study (Paola Torres Maldonado et al., 2011) revealed that "e-learning motivation" and "social influence" have a positive impact on individuals' willingness to participate in e-learning activities.

Similarly, according to Pintrich and Schrauben (1992), students' motivation degree is influenced by their significance to expected outcomes. This motivational factor propels their cognitive involvement, resulting in their involvement in use behavior. Thus, the following hypothesis is proposed:

H4: E-learning motivation has a significant impact on behavioral intention.

2.5 Perceived Usefulness

According to Davis (1989), perceived usefulness is the degree of belief an individual holds regarding the potential enhancement of their job performance or the accomplishment of work-related tasks through a specific technology. The concept of perceived usefulness involves individuals evaluating to what extent the incorporation of new technologies will improve their ability to perform tasks more effectively in a work environment (Lee, 2006). The results of prior research on Information and Communication Technology (ICT) suggest that the perceived usefulness factor significantly influences the formation of individuals' behavioral intention (Alwahaishi & Snášel, 2013). The Technology Acceptance Model (TAM) emphasizes that perceived usefulness strongly affects the behavioral intention to adopt information technology (Davis, 1989). Davis et al. (1992) carried out research demonstrating the importance of perceived usefulness as a pivotal factor in determining behavioral intention. Individuals with internet experience exert a greater influence on customers' behavioral intention (Castañeda et al., 2007). Yee (2013) has combined TAM with empirical research on users' motivations for using mobile commerce. The findings suggest a favorable impact of perceived usefulness on the intention to use the service. At the same time, the intention of experienced users to participate in mobile electronic commerce is notably influenced by perceived usefulness (Pipitwanichakarn & Wongtada, 2021). The e-learning system can be seen as a technological tool, and students will utilize it only if they are convinced it can improve their academic results. The enhancement in performance is gauged through criteria such as learning efficiency, effectiveness, and grade improvement. Thus, in the realm of e-learning, Perceived Usefulness pertains to the degree to which students trust that employing the e-learning system will boost their academic achievements. As a result, perceived usefulness will impact their inclination to embrace and incorporate the e-learning system, either directly or indirectly. Therefore, the following hypothesis was formed:

H6: Perceived usefulness has a significant impact on behavioral intention.

2.6 Behavioral Intention

Behavioral intention refers to the extent to which an individual is prepared or inclined to participate in and utilize a service (Yang et al., 2016). Behavioral intention is an individual's perceived probability of participating in a particular behavior (Ajzen, 1980). As Spears and Singh (2004) stated, behavioral intention refers to an individual's inclination to act in a certain way, influenced by their emotional state, cognitive processes, and assessment of past experiences. Previous researchers (Debnath et al., 2018; Tavares & Oliveira, 2018;) set up meaningful links associating the development of the UTAUT2 model with consumers' behavioral intentions. Several investigations have explored the correlation between behavioral intentions and use behavior within the context of e-learning systems. A study by Liaw et al. (2007) revealed that students' intentions to utilize e-learning systems positively impact their tangible usage patterns, leading to improvements in performance and satisfaction. Past research (Davis, 1989; Venkatesh & Davis, 2000; Venkatesh et al., 2003) has affirmed that individuals' actual use of electronic systems is directly influenced by their intentions to utilize these systems and the positive outcomes within the context of e-learning systems (Chang & Tung, 2008; Liu et al., 2010; Tarhini et al., 2017). Therefore, this study assumes:

H7: Behavioral intention has a significant impact on use behavior.

2.7 Use Behavior

Davis et al. (1989) and Venkatesh et al. (2003) defined use Behavior as the actions and implementation of blended learning approaches. Use Behavior refers to users' intensity level when interacting with technology (Awwad & Al-Majali, 2015). People's use behavior can be viewed as a concrete expression and implementation of their behavioral intentions (Ajzen, 1991). As Wut et al. (2021) described, the characterization of "use behavior" is relatively limited, with a specific emphasis on the utilization of mobile applications. Numerous research investigations have confirmed a notable correlation between behavioral intention and user behavior (AlAwadhi & Morris, 2008; Kijsanayotin et al., 2009; Wang & Shih, 2009). Farooq et al. (2017) recognized individual innovativeness within information technology as a consistent aspect of personal characteristics, fostering curiosity and drive to explore emerging technologies. This personal innovativeness significantly impacts users' intention to use and the practical use behavior of technology.

3. Research Methods and Materials

3.1 Research Framework

The conceptual framework proposed in this study is developed by analyzing previous research frameworks. Samsudeen and Mohamed (2019) present the first theoretical framework, investigating the influence of effort expectancy, motivation, and Internet experience on behavioral intention and use behavior. Paola Torres Maldonado et al. (2011) conducted the second theoretical framework, examining the impact of e-learning motivation on behavioral intention and use behavior. The third theoretical framework, undertaken by Lee (2006), explores the effects of subjective norms and perceived usefulness on behavioral intention and use behavior. The conceptual framework of this research is illustrated in Figure 1.

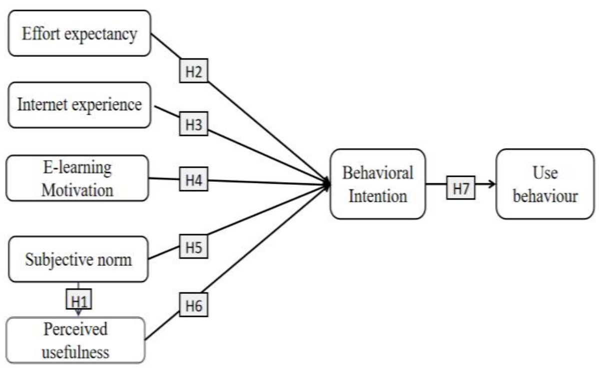

Figure 1: Conceptual Framework

H1: Subjective norm has a significant impact on perceived usefulness.
H2: Effort expectancy has a significant impact on behavior intention.
H3: Internet experience has a significant impact on behavior intention.
H4: E-learning motivation has a significant impact on behavioral intention.
H5: Subjective norm has a significant impact on behavioral intention.
H6: Perceived usefulness has a significant impact on behavioral intention.
H7: Behavioral intention has a significant impact on use behavior.

3.2 Research Methodology

This study employed a non-probability sampling method for conducting quantitative analysis. We distributed a survey to second-year students at Henan Vocational Institute of Arts who had experience with e-learning systems through WeChat and QQ groups, employing convenience sampling. The collected data were analyzed to identify the key factors significantly influencing the use behavior of e-learning systems. The survey consisted of three parts. Firstly, screening questions were used to identify the characteristics of the respondents. Secondly, a 5-point Likert scale was employed to analyze seven proposed variables, ranging from strongly disagree (1) to agree (5) with all seven hypotheses strongly. Lastly, demographic questions included gathering details on gender, grade, education, and occupation.

A pilot test involving 33 respondents was conducted, and the Item-Objective Consistency Index (IOC) was analyzed to ensure the precision of the survey questions. The Item-Objective Congruence (IOC) process ensures the validity of the assessment, with a criterion set at a score above 0.6. Moreover, the obtained Cronbach's Alpha score exceeded 0.7, signifying a dependable measurement of the intended construct and reinforcing the overall reliability of the test results (George & Mallery, 2003).

An evaluation using Cronbach's Alpha was conducted to guarantee the questionnaire's validity and reliability. Following the reliability test, 500 valid questionnaires were collected successfully. The precision of convergence and validity was confirmed through Confirmatory Factor Analysis (CFA). Furthermore, a comprehensive fit test was executed on the model to establish its validity and reliability. Ultimately, a Structural Equation Model (SEM) was employed to investigate the influence of variables.

3.3 Population and Sample Size

In this study, the target population refers to individuals who are specifically of interest to researchers (Malhorta & Birks, 2006). Saunders et al. (2016) define the target population as the main concentration of researchers and a subset within the broader population. Hair et al. (2010) underscores the significance of gathering data from individuals with similar characteristics to create a target group relevant to the research topic. According to Cooper and Schindler (2011), the target population contains individuals, records, and events associated with the study. Moreover, as stated by Burns and Grove (1997), individuals meeting specific selection criteria can be regarded as part of the target population.

This study's target population is second-year college students. The objective is to compare grade-level differences in e-learning systems. After the screening process, data from 500 second-year college students from each group will be selected for analysis to examine specific factors influencing the use behavior of e-learning systems.

3.4 Sampling Technique

In selecting research subjects, purposeful or judgmental sampling was employed in the initial phase, quota sampling in the second phase, and convenience sampling in the third phase. Therefore, researchers distributed questionnaires to second-year students at a public vocational college in Henan province, all of whom have experienced e-learning. The choice of target respondents in this study was deliberate and meaningful, allowing researchers to determine participant selection based on subjective judgment, ensuring consistency between the sample and research objectives.

Quota sampling was utilized to choose samples from each category in a balanced way, ensuring a representative representation of the entire population. Additionally, researchers determined the appropriate number of students based on the quota sampling design and proportional sample sizes.

Furthermore, the sampling units used in this study involved students from five different arts majors at Henan Vocational Institute of Arts (News Media major, Music major, Art major, Dance major, and Drama major), with 500 second-year college students selected as the final-stage sample.

Table 1: Sample Units and Sample Size

Undergraduates of arts majors	Population Size	Proportional Sample Size
The number of news media major students	987	151
The number of music major students	786	121
The number of art major students	752	115
The number of dance major students	440	67
The number of drama major students	297	46
Total	**3262**	**500**

Source: Constructed by author

4. Results and Discussion

4.1 Demographic Information

The demographic profile of the target survey group consisting of 500 sophomore students is detailed in Table 2. The respondents are sophomores from five arts majors at Henan Vocational Institute of Arts. Regarding gender, 39.6% of the students are male, and 60.4% are female. Regarding age, 84.4 are 18-20 years old, and 15.6% are 20-22 years old.

Table 2: Demographic Profile

Demographic and General Data (N=500)		Frequency	Percentage
Gender	Male	198	39.6%
	Female	302	60.4%
Age	18-20	422	84.4%
	20-22	78	15.6%

4.2 Confirmatory Factor Analysis (CFA)

In this research, Confirmatory Factor Analysis (CFA) was utilized. CFA, as a method for measuring latent variables (Byrne, 2013; Hoyle, 1995; 2011; Kline, 2010), distinguishes latent constructs from other variables and reveals the maximum variance shared with pertinent variables. Through this method, data dimensions are minimized, the scale of various indicators is standardized, and the inherent correlations within the dataset are explained. Researchers frequently rely on CFA to determine if their hypotheses find support in empirical data (Fox, 2010).

The results of the CFA conducted in this study indicate that all items within each variable are statistically significant and exhibit factor loadings supporting the discriminant validity of the measurement model. Following the recommendation of Fornell and Larcker (1981), the Composite Reliability (CR) exceeds the threshold of 0.7, and the Average Variance Extracted (AVE) surpasses the cutoff of 0.4. These finding results, as shown in Table 3, indicate that all variables in the study exhibit substantial internal consistency and reliability.

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
Subjective norm (SN)	Abbasi et al. (2011)	4	0.931	0.866-0.897	0.931	0.772
Effort expectancy (EE)	Samsudeen and Mohamed (2019)	3	0.876	0.822-0.852	0.876	0.702
Internet experience (IE)	Kim (2010)	3	0.906	0.848-0.897	0.906	0.763
E-learning motivation (ELM)	Paola Torres Maldonado et al. (2011)	4	0.934	0.862-0.897	0.934	0.780
Perceived usefulness (PU)	Abbasi et al.（2011）	5	0.953	0.876-0.909	0.953	0.803
Behavioral intention (BI)	Samsudeen and Mohamed (2019)	4	0.944	0.890-0.913	0.944	0.808
Use behavior (UB)	Abbasi et al. (2011)	4	0.941	0.882-0.904	0.941	0.801

To ensure the effectiveness of the research, analysis was carried out on the square root of the extracted average variance, ensuring that all correlations exceed the respective values for each variable, as detailed in Table 4. In conducting Confirmatory Factor Analysis (CFA), multiple fit indices, including GFI, AGFI, NFI, CFI, TLI, and RMSEA, were employed to assess the model's fit.

Table 4: Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	< 5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	658.920/303 or 2.175
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.912
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.891
NFI	≥ 0.80 (Wu & Wang, 2006)	0.948
CFI	≥ 0.80 (Bentler, 1990)	0.971
TLI	≥ 0.80 (Sharma et al., 2005)	0.967

Fit Index	Acceptable Criteria	Statistical Values
RMSEA	< 0.08 (Pedroso et al., 2016)	0.049
Model Summary		**Acceptable Model Fit**

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

This study's results, presented in Table 5, suggest that both convergent and discriminant validity exceed the acceptable thresholds. As a result, this study has effectively demonstrated the establishment of convergent and discriminant validity. Furthermore, these measurement outcomes not only confirm the discriminant validity but also provide validation for estimating subsequent structural models.

Table 5: Discriminant Validity

	SN	EE	IE	ELM	PU	BI	UB
SN	**0.879**						
EE	0.190	**0.838**					
IE	0.143	0.267	**0.873**				
ELM	0.186	0.357	0.332	**0.883**			
PU	0.232	0.333	0.327	0.414	**0.896**		
BI	0.417	0.312	0.289	0.373	0.428	**0.899**	
UB	0.177	0.368	0.367	0.465	0.492	0.453	**0.895**

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 the information provided by Hair et al. (2010), structural equation modeling (SEM) is a statistical approach employed for analyzing causal relationships among variables proposed in a model while also considering measurement errors associated with structural coefficients. The assessment of goodness-of-fit indicators for the SEM model is carried out, as demonstrated in Table 5.2.

According to Awang (2012) and Al-Mamary and Shamsuddin (2015), the chi-square/degrees of freedom (CMIN/DF) ratio, used to evaluate model fit, should be kept under 5. Additionally, based on Sica and Ghisi (2007), the Goodness of Fit Index (GFI) is recommended to surpass 0.85.

This study conducted SEM analysis and model adjustment using SPSS AMOS version 26. The results for fit indices are as follows: CMIN/DF = 3.244, GFI = 0.858, AGFI = 0.824, NFI = 0.922, CFI = 0.945, TLI = 0.936, RMSEA = 0.067. The acceptable values are presented in Table 6. These values were compared with the mentioned acceptable thresholds.

Table 6: Goodness of Fit for Structural Model

Fit Index	Acceptable Criteria	Statistical Values Before Adjustment	Statistical Values After Adjustment
CMIN/DF	< 5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	1073.751/317 or 3.387	986.301/304 or 3.244
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.849	0.858
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.819	0.824
NFI	≥ 0.80 (Wu & Wang, 2006)	0.915	0.922
CFI	≥ 0.80 (Bentler, 1990)	0.939	0.945
TLI	≥ 0.80 (Sharma et al., 2005)	0.932	0.936
RMSEA	< 0.08 (Pedroso et al., 2016)	0.069	0.067
Model Summary		**Unacceptable Model Fit**	**Acceptable Model Fit**

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

4.4 Research Hypothesis Testing Result

To examine the research model, regression weights and R2 variances were employed to assess the significance of each variable. The findings presented in Table 6 demonstrate that all hypotheses were supported at a significance level of p=0.05. Behavioral intention had the most significant impact on usage behavior, with a regression weight of 0.468. There were significant correlations among subjective norm and behavioral intention (β=0.347), perceived usefulness and behavioral intention (β=0.259), subjective norm and perceived usefulness (β=0.251), e-learning motivation and behavioral intention (β=0.187), effort expectancy and behavioral intention (β=0.115), as well as internet experience and behavioral intention (β=0.112). Therefore, the model effectively demonstrates the factors influencing the use behavior of e-learning systems, as detailed in Table 7.

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-value	Result
H1: SN→PU	0.251	5.370*	Supported
H2: EE→BI	0.115	2.697*	Supported
H3: IE→BE	0.112	2.681*	Supported
H4: ELM→BI	0.187	4.479*	Supported
H5: SN→BI	0.347	7.853*	Supported
H6: PU→BI	0.259	6.030*	Supported
H7: BI→UB	0.468	10.314*	Supported

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

Table 7 presents the following findings:

H1: Subjective norms significantly affect perceived usefulness, with a standard coefficient value of 0.251. This supports the previous research of Taylor and Todd (1995), Venkatesh and Davis (2000), and Hsu and Lu (2004), indicating that subjective norms greatly influence perceived usefulness when users choose to use e-learning systems.

H2：Effort expectancy significantly impacts behavioral intention, with a standard coefficient value of 0.115. This is consistent with the studies of Alalwan et al. (2006) and Herrero Crespo et al. (2017), which emphasized the substantial effect of effort expectancy on behavioral intention when users choose to use e-learning systems. This is considered a key determinant of the intention to use e-learning systems.

H3: Internet experience significantly impacts behavioral intention, with a standard coefficient value of 0.112. This finding is consistent with the research of Chen and Macredie (2005), Ali et al. (2015), Abbad et al. (2011), and Speier and Venkatesh (2002), who found that internet experience affects behavioral intention. Alenezi and Karim (2010) discovered that the correlation between the intention to use the internet experience is stronger, influenced by the level of personal experience.

H4：E-learning motivation significantly impacts behavioral intention, with a standard coefficient value of 0.187. This result is consistent with past studies by Paola Torres Maldonado et al. (2011) and Coovert and Goldstein (1980), which emphasized that e-learning motivation affects behavioral intentions. Earlier research by Davis et al. (1992) and Moon and Kim (2001) established that extrinsic and intrinsic motivation plays an important role in influencing an individual's willingness to utilize information technology systems.

H5: Subjective norm significantly impacts behavioral intention, with a standardized coefficient value of 0.347. This result is consistent with the study by Yau and Ho (2015). Subjective norm is a crucial factor influencing learners' willingness to engage in e-learning. Therefore, subjective norm influences behavioral intention. According to Yau and Ho (2015), subjective norms influence learners' inclination to utilize e-learning.

H6: Perceived usefulness significantly affects behavioral intention, with a standardized coefficient 0.259. This finding is consistent with Yee (2013) and Pipitwanichakarn and Wongtada (2021) research, which indicates that perceived usefulness significantly influences behavioral intention.

H7: Behavioral intention significantly affects use behavior, with a standardized coefficient of 0.468. This finding is consistent with the research of Tarhini et al. (2017a), Tarhini et al. (2016), Liu et al. (2010), and Chang and Tung (2008). The research emphasizes the significant impact of behavioral intention on use behavior. The willingness of students to use e-learning systems positively influences their actual use behavior.

These findings provide valuable insights into the factors influencing behavioral intention and use behavior regarding e-learning systems.

5. Conclusion and Recommendation

5.1 Conclusion and Discussion

This study primarily investigates the factors influencing the use behavior of sophomore students at Henan Vocational Institute of Arts using e-learning systems. A series of hypotheses were proposed, and a conceptual framework was developed to examine how subjective norms, effort expectation, internet experience, e-learning motivation, perceived usefulness, and behavioral intention significantly affect the use behavior of e-learning systems. The researchers designed a survey questionnaire distributed to the sophomore students at Henan Vocational Institute of Arts with experience in the e-learning system, serving as the target sample for the study. Confirmatory Factor Analysis (CFA) was employed to assess and validate the effectiveness and reliability of the conceptual model. Additionally, Structural Equation Modeling (SEM) was applied to analyze various factors that influence the use behavior of e-learning systems.

The study's findings suggest that subjective norms play a crucial role in influencing the perceived usefulness of e-learning systems. Lee (2006) highlighted the significance of subjective norms in shaping technology adoption. This impact may be directly or indirectly suggested through the perceived usefulness within the working environment (Hsu & Lu, 2004). Secondly, the effort expectations significantly influence students' behavioral intentions in e-learning systems. According to Chua et al. (2018), the importance of effort expectations lies in their role in determining both the intention to use technology and the actual utilization of technology.

Additionally, Zhou et al. (2010), employing the Unified Theory of Acceptance and Use of Technology (UTAUT) framework, underscored the direct link between effort expectations and behavioral intentions. Thirdly, internet experience positively influences behavioral intentions in the context of an e-learning system. Internet experience is another factor affecting students' behavioral intention to use e-learning systems, which implies that the more experience students have with the internet, the longer the duration of each internet visit, and the higher the frequency of internet use, the more likely they are to use e-learning systems. Fourthly, students' motivation for e-learning significantly influences their behavioral intentions within e-learning systems. Research indicates that in this learning model, the level of students' motivation is crucial (Conati, 2002). The students' motivation level not only affects their enthusiasm for e-learning but also significantly impacts their participation and level of engagement within the system. Therefore, understanding and promoting students' learning motivation is crucial for enhancing the effectiveness of e-learning systems and improving students' learning outcomes. Fifthly, Students' subjective norms positively impact their behavioral intentions within e-learning systems. Yau and Ho (2015) point out that subjective norms play a crucial role in shaping learners' behavioral intentions to use e-learning and emphasize their influence on behavioral intentions. Subjective norms involve individuals' perceptions of others' expectations and social pressures, particularly within a learning environment. Students tend to shape their behavioral intentions based on norms they consider important or socially accepted, a phenomenon especially pronounced in e-learning. Therefore, understanding and considering subjective norms are important in promoting students' adoption and effective utilization of e-learning systems.

Sixthly, students' perceived usefulness of e-learning systems has a significant and far-reaching impact on their behavioral intentions. When students perceive the system as having practical utility in improving their learning outcomes, they are inclined to adopt and use e-learning systems more actively. Finally, students' behavioral intentions have profound implications for the use behavior of e-learning systems. The research by Samsudeen and Mohamed (2019) indicates that elements of the UTAUT2 model significantly and critically influence both the behavioral intentions and actual use behavior within e-learning systems. Behavioral intentions are key in influencing students' use behavior within e-learning systems. This suggests that students' intentions and expectations regarding e-learning systems directly impact their eventual use behavior. Therefore, in designing and promoting e-learning systems, understanding and guiding students' behavioral intentions are crucial to ensure the systems' successful adoption and effective utilization.

5.2 Recommendation

The study found that important factors influencing the behavioral intention and use behavior of e-learning among college students at Henan Vocational Institute of Arts include subjective norms, effort expectations, internet experience, e-learning motivation, and perceived usefulness. In the first place, individuals' perceptions of others' expectations and social pressure play a crucial role in the learning environment. Students tend to shape their behavioral intentions based on important or socially acceptable norms. In the second place, students' expectations of technology use are crucial in determining behavioral intentions and actual technology usage. In third place, the longer and more frequent students use the internet, the more likely they are to use the e-learning system. The level of motivation not only affects their enthusiasm for e-learning but has an important impact on their participation and engagement in the system. The positive impact of subjective norms is also emphasized, indicating that students' subjective norms positively influence behavioral intentions in the e-learning system. Subjective norms involve individuals' perceptions of others' expectations and social pressure, especially in the learning environment. Students' perception of the usefulness of the e-learning system directly or indirectly affects their attitudes and acceptance levels, thus influencing their adoption intentions. Lastly, behavioral intentions for learning have a profound impact on the usage behavior of the e-learning system. Students' intentions and expectations for using the e-learning system directly influence their usage behavior.

The study emphasizes the importance of subjective norms, effort expectations, internet experience, e-learning motivation, perceived usefulness, and behavioral intentions in influencing students' use behavior in e-learning systems. These results are crucial for designing and promoting e-learning systems to enhance successful adoption and effective utilization. They can better meet students' needs, improve user experience, and encourage active participation and utilization of e-learning systems. These research findings provide valuable guidance for developing strategies to enhance the adoption and effective use of e-learning systems.

5.3 Limitation and Further Study

The study has limitations, including sample specificity, cultural differences, self-report bias, time factors, and a need for in-depth exploration of complex relationships between variables. The study's limitations are primarily reflected in the choice of sophomore students majoring in five arts departments at Henan Vocational Institute of Arts as the population and sample. This may produce different analytical results when investigating various schools, majors, grades, regions, or countries. Future research could further examine other factors that may influence the use behavior of e-learning systems, such as course attributes, convenience conditions, social influences, gender, and region.

Additionally, to enhance the validity and objectivity of research results, it is recommended that future studies validate findings in a more diverse student population, conduct comparisons across different majors, use objective performance indicators, and consider factors like temporal changes. Moreover, future research should comprehensively analyze subjective norms, effort expectations, internet experiences, perceived usefulness, and learning motivation to understand students' use behavior in e-learning systems. Such in-depth analysis will provide targeted recommendations for more effective educational technology and policy design.

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