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Factors Influencing Use Behavior of E-Learning Systems Among Junior Students Majoring in Arts at Higher Vocational Colleges in Henan, China

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Abstract

Purpose: This research aims to investigate the factors influencing the use behavior of the e-learning system among junior students of arts majors in higher vocational colleges in Henan, China. The conceptual framework of the study includes subjective norm, effort expectancy, internet experience, e-learning motivation, perceived usefulness, behavioral intention, and use behavior. **Research design, data, and methodology:** The quantitative research method was used to distribute survey questionnaires to 500 junior students pursuing arts majors at a public higher vocational college in Henan, China. The initial assessment of the content validity and reliability in the research survey included using Item Objective Consistency and Cronbach's Alpha. Confirmatory Factor Analysis and Structural Equation Modeling were utilized to examine the data, verify the model fit, and establish causal relationships between variables. This procedure aimed to assess the hypotheses for both their reliability and validity. **Results:** The findings of the study suggest that the use behavior of e-learning systems among junior students majoring in arts at vocational colleges in Henan is significantly affected by subjective norm, effort expectancy, internet experience, e-learning motivation, perceived usefulness, and behavioral intention. **Conclusions:** This study contribute to better meeting student needs, improving user experience, and fostering active engagement and full utilization of e-learning systems.

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

JEL Classification Code: E44, F31, F37, G15

1. Introduction

In modern China, technology plays a crucial role in daily life, making professionals, educators, and learners reexamine their core beliefs to use technology to reimagine or improve education and training systems. At the same time, these technological tools offer a range of advantages for both students and teachers. The traditional education system is built on face-to-face learning and interaction, considering teachers as central figures of knowledge (Khan & Qudrat-Ullah, 2021).

With the evolution of time, instructional technology has shifted from traditional teaching methods to distance learning modes. This transformation has changed the learning methods and redefined the roles and responsibilities within education. The development of information technology has facilitated global communication, with tools evolving from traditional slide presentations to today's web-based calculators (Gilbert & Green, 1994). This evolution of technology has enhanced teaching efficiency and provided learners with a more flexible and personalized learning experience.

For a long time, higher education in China has adhered to a traditional teaching model, where professors deliver lectures and students take notes. In this conventional approach, communication between teachers and students has been regarded as a crucial component of knowledge dissemination. However, innovative education delivery systems have gradually emerged, including interactive and reflective learning approaches (Haverila & Barkhi, 2009),

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challenging traditional educational attitudes.

The new technologies bring many new features to teaching, which can be applied to make teaching more attractive (Keller & Suzuki, 2004). Interactive and reflective learning methods emphasize the importance of student participation and thinking, which sharply contrasts with the traditional one-way knowledge transmission. This transformation prompts educators to rethink teaching methods and provides students with a richer and deeper learning experience.

Everyone must possess fundamental technological knowledge and recognize it as a tool for attaining educational objectives. This encourages educational institutions to adopt innovative technologies to actively enhance the teaching process. Previous studies (Gladstone, 2000; Reeder et al., 2004; Weller, 2004) widely acknowledge the successful application of Information Technology (IT) in education. Students have increasingly high expectations for the existence and use of information technology in higher education (Roberts, 2004). Some educational institutions use information technology as a competitive advantage to draw more students into the highly competitive higher education market.

E-learning has significantly reshaped traditional educational methods, serving as a potent tool. It boosts educational institutions' instructional and learning capacities by providing efficient and productive channels for delivering instruction to students and disseminating knowledge (Alfraih & Alanezi, 2016). E-learning uses information technology to reach educational resources and methods, covering the procedures of learning, teaching, and acquiring knowledge at any time and from any location (Turban et al., 2015). This learning method can occur through various modes, including online, offline, or in a blended format (Al-Busaidi, 2013). Considering time and space considerations, e-learning provides learners with the convenience and flexibility to access and use knowledge delivered in digital form (Tetteh, 2016). Driscoll (2010) contends that e-learning has strategic and technological benefits. Furthermore, e-learning encourages continuous learning and self-renewal by allowing individuals to participate in unconventional learning approaches (Turban et al., 2015).

During the widespread outbreak of the 2019 coronavirus, numerous countries experienced significant impacts in various sectors such as education, tourism, social life, and the economy (Baldwin & Tomiura, 2020; Nicola et al., 2020). In the face of the challenges posed by the COVID-19 pandemic, e-learning emerged as a crucial education means. This global health crisis forced 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 over the Internet, participate in remote learning activities, and engage in online interactions and discussions with teachers and peers.

Teachers can assign online assignments and quizzes to students through the e-learning system, and students can complete these tasks and exams on the platform, receiving timely feedback. The e-learning system also offers mobile applications, allowing students to access course content anytime, anywhere, through their smartphones or tablets, facilitating electronic learning.

Considering the trend of widespread adoption of e-learning systems, researchers, taking this as a background, selected junior students majoring in the arts at Henan Vocational Institute of Arts as the study subjects. The researcher conducted a detailed analysis of the factors influencing their use behavior of the e-learning system. E-learning is acknowledged for its ability to meet the individual needs of learners. E-learning plays a crucial role in the digital age by effectively promoting the transfer of knowledge, as it prioritizes the individual needs of learners rather than the demands of educational institutions or teachers (Huang & Chiu, 2015).

2. Literature Review

2.1 Subjective Norm

The subjective norm of an individual can be described as their recognition and approval of a particular behavior within a socially significant reference group (Fishbein & Ajzen, 1975). Subjective norm involves an individual’s comprehension of the social stress or expectations established by others regarding a specific behavior. These norms can affect an individual’s behavior and tendency to participate in a particular action (Venkatesh & Davis, 2000). Lee (2006) highlighted that earlier studies have accumulated substantial theoretical and empirical support, emphasizing the significance of subjective norms in shaping the adoption of technology. This impact can manifest directly or indirectly through the perceived usefulness in the work environment (Hsu & Lu, 2004). In the Theory of Reasoned Action, the subjective norm is one factor influencing behavioral intention.

Additionally, the Theory of Planned Behavior and the Theory of Reasoned Action include a component called subjective norm, indicating how behavioral intentions are influenced by it, thereby affecting behavior (Hsu & Lu, 2004). Several investigations have affirmed the importance of subjective norms. Current research suggests that subjective norm is a vital element that affects learners’ willingness to engage in e-learning.

Consequently, subjective norms are critical in shaping behavioral intentions (Yau & Ho, 2015). Therefore, this study contains the subjective norm regarding using e-learning systems. Subjective norms can positively influence behavioral intentions (Grandón et al., 2011; Hansen et al., 2004; Lam & Hsu, 2006). Based on the findings above, the hypothesis is set as follows:

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

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

2.2 Effort Expectancy

According to Yadav et al. (2016), effort expectancy refers to an individual's belief in their ability to use a technology without additional endeavor. As defined by Yu (2012), effort expectancy indicates the level of comfort and ease that an individual experiences when employing a specific technology. Effort expectancy assesses the effort required to attain proficiency in using technology (Tai & Ku, 2013). The study by Chiwara et al. (2017) proposes that factors like usefulness, flexibility, and user-friendliness play a role in shaping the concept of effort expectancy. Effort expectancy indirectly affects behavioral intention by positively influencing performance expectancy, positively impacting behavioral intention (Alalwan et al., 2016; Herrero & San Martín., 2017; Oliveira et al., 2016).

In a recent study conducted in Taiwan by Chou et al. (2018), it was discovered that effort expectancy significantly influences consumers' behavioral intention within the context of mobile commerce. Prior research has emphasized the importance of effort expectancy in determining the intention to use and the actual usage of technology (Chua et al., 2018). Therefore, the above findings allow hypotheses to be established:

H2: Effort expectancy has a significant impact on behavior intention.

2.3 Internet Experience

Alenezi et al. (2010) described internet experience as the degree of skill and familiarity an individual has in accomplishing tasks through the internet.

According to Chang (2004), internet experience involves the range of practical skills and personal familiarity that an individual possesses, allowing them to proficiently accomplish specific tasks by effectively using the internet. Johnson and Kaye (2009) defined internet experience as measuring respondents' online activities and their internet use time. According to Chen and Macredie (2005), internet experience plays a crucial role in facilitating the effective use of website applications, as individuals with typically more internet experience tend to exhibit a more positive attitude towards website usage. Alenezi et al. (2010) found that the impact of an individual's experience level is more evident in the correlation between the willingness to use the internet and one's experience level. The impact of experience on students' willingness to use Internet technology is complex and multifaceted. The level and speed of experience significantly affect the intention to use specific systems. With increased Internet experience, individuals' perceptions of using e-learning systems also enhance (Hackbarth et al., 2003). Research by Liao and Cheung (2001) indicates that Internet experience is the most crucial factor determining users' willingness to engage in electronic shopping. It plays a significant role in influencing their behavior in using electronic shopping systems. This study attempts to position Internet experience as an important factor influencing the behavior intention toward e-learning systems. Therefore, the following hypotheses are proposed:

H3: Internet experience has a significant impact on behavior intention.

2.4 E-learning Motivation

Paola Torres Maldonado et al. (2011) defined the concept of e-learning motivation as students' inclination to perceive e-learning systems as valuable and easy to operate, along with their positive desire to pursue and gain academic advantages offered by these systems actively. In e-learning, students' motivation is crucial (Conati, 2002). Learning motivation is characterized as the tendency of students to perceive academic activities as meaningful and valuable and to exert effort in obtaining the expected academic benefits from these activities (Brophy, 2004). Vallerand et al. (1992) defined extrinsic motivation as the pursuit of goals to achieve outcomes rather than being driven by the inherent value of the activity. In contrast, Vallerand et al. (1992) defined intrinsic motivation as the experience of joy and satisfaction derived from engaging in an activity. Extrinsic motivation involves undertaking an activity to attain expected outcomes or results. It is driven by a belief that the activity is a means to achieve valuable goals.

The study by Afzal et al. (2010) indicates that both extrinsic and intrinsic motivation positively affect students' academic performance. Additionally, e-learning is a significant tool that educators can use to enhance student motivation and facilitate their learning processes (Mateo et al., 2010). Harandi's (2015) research indicates that a supportive e-learning environment helps to enhance learning motivation. The motivation of teachers and the role of education play a vital part in the success of e-learning (Keramati et al., 2011). As a result, the following hypotheses are suggested:

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

2.5 Perceived Usefulness

Perceived usefulness is defined as an individual's belief in the ability of a particular system to enhance its efficiency in the workplace (Mishra et al., 2023). According to Kim et al. (2019), assessing technological products and services relies significantly on the crucial role of perceived usefulness as a critical metric or indicator. The concept of perceived usefulness associated with e-learning depends on individuals' belief in the extent to which e-learning can substantially contribute to helping them achieve their goals (Lin et al., 2011). Venkatesh and Davis (2000) found a positive association between perceived usefulness and the intention of students to utilize e-learning. Numerous studies have provided empirical evidence supporting the idea that the perceived usefulness of online reviews plays a crucial role in shaping the intention to make a purchase (Hu & Yang, 2021). The foundational role of perceived usefulness in forecasting the acceptance and usage of information technology has received substantial empirical support from a variety of studies (Davis, 1989; Davis et al., 1992; Gefen, 2003; Gefen & Straub, 1997, 2000; Hsu & Lu, 2004; Igbaria et al., 1997; Ong et al., 2004; Venkatesh & Davis, 2000) Therefore, based on the findings above, the assumption is set as follows:
H6: Perceived usefulness has a significant impact on behavioral intention.

2.6 Behavioral Intention

According to Ghosh et al. (2023), behavioral intention is defined as the inclination of individuals to obtain products or services from similar providers and convey their thoughts and emotions about those products or services to people they know. Behavioral intention involves the tendency to purchase specific services or products from the same supplier and subsequently share one's experiences with close acquaintances and family members (Ghosh et al., 2023). Fishbein (1967) suggested that behavioral intention can be understood as deliberate action, a motivating element that stimulates individuals to involve themselves actively in particular activities. According to Filieri et al. (2021), behavioral intention can be an observable buying conduct or a diagnostic instrument that assists in comprehending consumer behavior. Additionally, according to the research by Venkatesh et al. (2003), behavioral intention positively impacts the usage of systems. Kijsanayotin et al. (2009) argue that behavioral intention can predict actual use behavior. According to the explanation provided by Triandis (1989), behavioral intention can be compared to self-guidance, allowing individuals to participate in specific activities. Casaló et al. (2010) argue that behavioral intention is crucial in determining actual behavior. Hence, the following hypothesis is established:
H7: Behavioral intention has a significant impact on use behavior.

2.7 Use Behavior

According to Venkatesh et al. (2008), the features of use behavior point to the regularity, duration, and intensity of an individual's interaction with a particular system. User Behavior is defined as the cognitive and physical actions carried out by individuals by applying their current knowledge and personal experiences (Ukut & Krairit, 2019). Kim et al. (2007) argue that use behavior primarily reflects individuals' skills in utilizing information systems, including the breadth, characteristics, and frequency of information system utilization. Yeop et al. (2019) indicate that behavioral intention has a substantial positive influence on the use behavior of innovative information systems. Samsudeen and Mohamed (2019) discovered that the components of UTAUT2 play a significant and vital role in influencing both behavioral intentions and use behavior within e-learning systems. Behavioral intention determines users' willingness to adopt e-learning systems (Salloum & Shaalan, 2019). Behavioral intention is a precursor to actual use behavior and indicates users' willingness to perform a specific action. According to the Technology Acceptance Model (TAM) proposed by Davis (1989), behavioral intention is a key determinant of actual system usage. The model suggests that individuals who perceive a system as useful and easy to use are more likely to develop a positive intention to use it, increasing the chance of actual use.

3. Research Methods and Materials

3.1 Research Framework

The conceptual framework introduced in this study is constructed by analyzing previous research frameworks. The initial theoretical framework, presented by Samsudeen and Mohamed (2019), delves into the influence of effort expectancy, motivation, and Internet experience on behavioral intention and use behavior. The second theoretical framework, conducted by Paola Torres Maldonado et al. (2011), examines 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. Figure 1 illustrates the conceptual framework employed in this research.

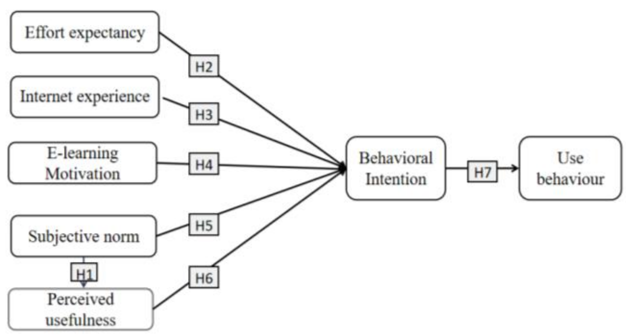

Figure 1: Conceptual Framework

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

For quantitative analysis, this study utilized a non-probability sampling method. We surveyed junior college students with experience in e-learning systems at Henan Vocational Institute of Arts. The survey was distributed through WeChat and QQ groups, employing convenience sampling. The collected data were analyzed to identify the main factors that substantially influence the use behavior of e-learning systems. The survey consisted of three segments. Firstly, screening questions were utilized to determine the characteristics of the respondents. Secondly, a 5-point Likert scale was utilized to analyze seven suggested variables, spanning from a rating of strongly disagree (1) to strongly agree (5) with each of the seven hypotheses. Finally, demographic questions contained comprehensive details regarding gender, grade level, educational achievement, and occupation. A pilot test, which engaged 33 respondents, was carried out, and the Item-Objective Congruence (IOC) analysis was performed to guarantee the precision of the survey queries.

In order to ensure the validity and reliability of the questionnaire, an assessment was conducted utilizing Cronbach's Alpha approach. 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).

After the reliability test, 500 valid surveys were successfully gathered. The accuracy of convergence and validity was verified by implementing Confirmatory Factor Analysis (CFA). Moreover, A comprehensive fitting test was carried out to verify the reliability and validity of the model. Finally, the structural equation model (SEM) was used to study the influence of the variables.

3.3 Population and Sample Size

This research's target population comprises individuals, records, and events linked to the study (Cooper & Schindler, 2011). Saunders et al. (2016) define the target population as the primary focus of researchers and a subgroup within the larger population. Hair et al. (2010) stressed the importance of collecting data from individuals with similar characteristics to form a target group corresponding to the research topic. The target population is defined as individuals who are the specific focus of interest for the researchers (Malhorta & Birks, 2006). Furthermore, according to Burns and Grove (1997), individuals who meet specific selection criteria can be considered as belonging to the target population.

This study divides the target population into two groups: sophomore and junior college students. The goal is to assess the differences in e-learning systems among different academic stages. After the screening process, we will collect data from 500 third-year students in each group to analyze specific factors influencing the use behavior of e-learning systems.

3.4 Sampling Technique

The research subject selection process involves three distinct phases: purposive or judgmental sampling in the first, quota sampling in the second, and convenience sampling in the third. For the questionnaire survey conducted among junior college students at a public vocational college in Henan province during the third phase, all participants were required to possess extensive experience with e-learning systems.

The thoughtful and meaningful selection of target respondents in this study involves purposive or judgmental sampling in the first phase, allowing researchers to use subjective judgment to ensure alignment between the sample and the research objectives. To enhance the representativeness of the entire population, quota sampling was employed in the second phase, ensuring a balanced selection of samples from each category and determining an appropriate number of students to maintain proportional sample sizes.

In addition, the sampling units for this study comprised students from five distinct arts majors at the Vocational Institute of Arts, namely News Media major, Music major, Art major, Dance major, and Drama major. Five hundred junior college students were selected from these majors 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	1121	167
The number of music major students	797	119
The number of art major students	728	109
The number of dance major students	435	65
The number of drama major students	269	40
Total	**3350**	**500**

Source: Constructed by author

4. Results and Discussion

4.1 Demographic Information

The demographic profile of the target survey population, consisting of 500 junior students, is outlined in Table 2. These respondents are from five arts majors at Henan Vocational Institute of Arts. In terms of majors, students majoring in News Media account for 33.4%, followed by those in Music at 23.8%, Art at 21.8%, Dance at 13%, and Drama at 8%. Regarding gender, male students make up 41.4%, while female students account for 58.6%. Students aged 18-20 make up 54.8%, while those aged 21-22 make up 45.2%.

Table 2: Demographic Profile

Demographic and General Data (N=500)		Frequency	Percentage
Undergraduates of arts majors (sophomore students)		500	100%
Gender	Male	207	41.4%
	Female	293	58.6%
Major	News Media Major	167	33.4%
	Music Major	119	23.8%
	Art Major	109	21.8%
	Dance Major	65	13%
	Drama Major	40	8%
Age	18-20	274	54.8%
	20-22	226	45.2%

4.2 Confirmatory Factor Analysis (CFA)

This study utilized Confirmatory Factor Analysis (CFA) to assess latent variables (Byrne, 2013; Hoyle, 1995, 2011; Kline, 2010). CFA distinguishes latent constructs from other variables, uncovering the maximum shared variance with related variables. The method facilitates data dimension reduction, standardization of indicator scales, and elucidation of internal correlations within the dataset. Hence, researchers often turn to CFA, as Fox (2010) suggested, to validate whether their hypotheses align with empirical data.

Through the application of CFA in this research, it was determined that each item within every variable holds statistical significance, and the factor loadings support the discriminant validity of the measurement model. By the recommendations of Fornell and Larcker (1981), the Composite Reliability (CR) exceeded the 0.7 threshold, and the Average Variance Extracted (AVE) surpassed the 0.4 cutoff. The outcomes presented in Table 3 indicate that all variables examined in the study exhibit significant 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	0.917	0.778-0.899	0.918	0.737
Effort expectancy (EE)	Samsudeen and Mohamed (2019)	3	0.939	0.899-0.935	0.940	0.838
Internet experience (IE)	Kim (2010)	3	0.927	0.84-0.944	0.929	0.813
E-learning motivation (ELM)	Paola Torres Maldonado et al. (2011)	4	0.960	0.89-0.957	0.960	0.857
Perceived usefulness (PU)	Abbasi et al.（2011）	5	0.972	0.907-0.955	0.972	0.874
Behavioral intention (BI)	Samsudeen and Mohamed (2019)	4	0.967	0.916-0.961	0.967	0.879
Use behavior (UB)	Abbasi et al. (2011)	4	0.970	0.923-0.965	0.970	0.888

To guarantee the efficacy of the study, an examination was conducted on the square root of the extracted average variance, confirming that all correlations surpass the respective values for every variable, as specified in Table 4. Furthermore, during the execution of CFA, a range of fit indices, such as GFI, AGFI, NFI, CFI, TLI, and RMSEA, were utilized to evaluate 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)	1078.942/305 or 3.538
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.858
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.824
NFI	≥ 0.80 (Wu & Wang, 2006)	0.934
CFI	≥ 0.80 (Bentler, 1990)	0.952
TLI	≥ 0.80 (Sharma et al., 2005)	0.945
RMSEA	< 0.08 (Pedroso et al., 2016)	0.071
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	**0.858**						
EE	0.353	**0.916**					
IE	0.165	0.144	**0.902**				
ELM	0.284	0.375	0.142	**0.926**			
PU	0.291	0.339	0.102	0.318	**0.935**		
BI	0.384	0.34	0.369	0.331	0.323	**0.938**	
UB	0.306	0.313	0.045	0.295	0.255	0.286	**0.943**

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

4.3 Structural Equation Model (SEM)

As per Hair et al. (2010), Structural Equation Modeling (SEM) is a statistical technique employed to analyze the causal relationships among variables proposed in a model, considering measurement errors associated with structural coefficients. The researcher assesses the goodness-of-fit indicators for the SEM model, as listed in Table 6. Consistent with the recommendations of Awang (2012) and Al-Mamary and Shamsuddin (2015), it is advisable to maintain the chi-square/degrees of freedom (CMIN/DF) ratio below 5 when evaluating model fit. Additionally, following the guidance of Sica and Ghisi (2007), it is suggested that the Goodness of Fit Index (GFI) should exceed 0.85.

In this study, Structural Equation Modeling (SEM) analysis and model adjustments were conducted using SPSS AMOS version 26. The outcomes of fit indices are presented: CMIN/DF = 3.538, GFI = 0.858, AGFI = 0.824, NFI = 0.934, CFI = 0.952, TLI = 0.945, RMSEA = 0.071. The acceptable thresholds for these values are provided in Table 6, and a comparison between these values and the specified acceptable thresholds was conducted.

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)	1170.966/317 or 3.694	1078.942/305 or 3.538
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.845	0.858
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.815	0.824
NFI	≥ 0.80 (Wu & Wang, 2006)	0.929	0.934
CFI	≥ 0.80 (Bentler, 1990)	0.947	0.952
TLI	≥ 0.80 (Sharma et al., 2005)	0.941	0.945
RMSEA	< 0.08 (Pedroso et al., 2016)	0.073	0.071
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

As presented in Table 7, the results indicate that at a significance level of p=0.05, all hypotheses received support. Internet experience has the most significant impact on use behavior, with a regression weight of 0.309. There is a significant correlation between subjective norm and behavioral intention (β=0.248), perceived usefulness and behavioral intention (β=0.155), subjective norm and perceived usefulness (β=0.305), e-learning motivation and behavioral intention (β=0.152), effort expectancy and behavioral intention (β=0.142), and behavioral intention and use behavior (β=0.283). Thus, the model effectively illustrates the factors influencing the use behavior of e-learning, as depicted in Table 7.

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-value	Result
H1: SN→PU	0.304	6.597*	Supported
H2: EE→BI	0.142	3.429*	Supported
H3: IE→BE	0.309	7.247*	Supported

Hypothesis	(β)	t-value	Result
H4: ELM→BI	0.152	3.713*	Supported
H5: SN→BI	0.248	5.554*	Supported
H6: PU→BI	0.155	3.605*	Supported
H7: BI→UB	0.283	6.276*	Supported

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

Table 7 presents the following findings:

H1: Subjective norms significantly impact perceived usefulness, with a standardized coefficient value of 0.304. This finding corroborates previous research by Hsu and Lu (2004). When users decide whether to use an e-learning system, subjective norms influence perceived usefulness.

H2: Effort expectancy significantly influences behavioral intention, with a standardized coefficient 0.142. This result aligns with studies by Alalwan et al. (2016), Herrero Crespo et al. (2017), Oliveira et al. (2016), and Chou et al. (2018). When users decide to use an e-learning system, effort expectancy substantially impacts behavioral intention and is considered crucial in determining behavioral intention to use e-learning systems.

H3: Internet experience significantly influences behavioral intention, with a standardized coefficient value 0.309. This research finding is consistent with the study by Liao and Cheung (2001), which also observed the impact of internet experience on behavioral intention. Additionally, Alenezi et al. (2010) further pointed out that, under the influence of individual experience levels, the correlation between internet experience and behavior intention is even more pronounced.

H4: E-learning motivation significantly influences behavioral intention, with a standardized coefficient value of 0.152. This research finding is consistent with previous studies. Paola Torres Maldonado et al. (2011) and Coovert and Goldstein (1980) indicate the influential role of electronic learning motivation on behavioral intention.

H5: Subjective norms significantly influence behavioral intention, with a standardized coefficient value 0.248. This research finding is consistent with studies by Grandón et al. (2011), Lam and Hsu (2006), and Hansen et al. (2004), highlighting the important role of subjective norms in behavioral intention. Yau and Ho (2015) particularly emphasize that subjective norms are a crucial factor influencing learners' behavioral intention to adopt e-learning.

H6: Perceived usefulness significantly influences behavioral intention, with a standardized coefficient 0.155. This finding is consistent with Yee's (2013) and Hu and Yang's (2021) research results. The studies indicate that perceived usefulness is important in significantly influencing behavioral intention.

H7: Behavioral intention significantly influences use behavior, with a standardized coefficient value 0.283. This research finding aligns with studies by Venkatesh et al. (2003), Kijsanayotin et al. (2009), and Casaló et al. (2010). The research emphasizes the crucial impact of behavioral intention on use behavior.

These findings provide valuable perspectives into the factors that influence users' behavioral intention to adopt e-learning and their actual use behavior.

5. Conclusion and Recommendation

5.1 Conclusion and Discussion

The research findings indicate that subjective norms significantly influence the perceived usefulness of e-learning systems. Lee (2006) underscores the significance of subjective norms in shaping technological adoption. Researchers point out that this influence is not merely a theoretical concept but can also occur directly or indirectly through the perceived usefulness in the work environment (Hsu & Lu, 2004). As a form of social influence, subjective norms can shape individuals' attitudes and beliefs toward technology adoption, affecting their perceived usefulness of e-learning systems. Thus, this finding highlights the crucial role of subjective norms in driving the adoption of e-learning systems.

Furthermore, Chua et al. (2018) point out that the perceived effort has significant implications for determining both the behavioral intention to use technology and actual technological use behavior. Zhou et al. (2010) applied the Unified Theory of Acceptance and Use of Technology (UTAUT) framework, emphasizing the direct link between effort expectation and behavioral intention. These research findings suggest that when technology is perceived as user-friendly and accessible, students are likelier to adopt it actively, potentially enhancing actual use behavior rates. This relationship becomes particularly crucial in the increasingly prevalent educational environment of e-learning systems, as user experience is paramount for successful adoption and effective utilization.

Thirdly, internet experience has a positive influence on shaping behavioral intentions within the e-learning environment. Internet experience is another crucial factor affecting students' behavioral intentions to use e-learning systems. This indicates that as students gain more experience using the Internet, spend more time on each visit, and increase the frequency of Internet usage, they are more likely to adopt e-learning systems actively. Fourthly, in the e-learning environment, students' e-learning motivation significantly affects their behavioral intention in the e-learning system. Under this learning model, research shows that students' motivation level in e-learning is extremely important (Conati, 2002). In other words, the level of motivation of students has an impact not only on their motivation in e-learning but also on their level of participation and investment in the system. Therefore, it is very important to understand and promote students' e-learning motivation to improve the effectiveness of the e-learning system and students' learning performance. Fifthly, students' behavioral intentions in e-learning systems are positively influenced by their subjective norms. The study of Yau and Ho (2015) emphasized the key role of subjective norms in shaping learners' behavioral intention to adopt e-learning. It emphasized that subjective norms have an important impact on behavioral intention. This means that students are more inclined to form their intention to use the e-learning system based on their perception of the expectations of others and social pressure. Therefore, it is important to recognize and consider subjective norms to motivate students to adopt and effectively utilize e-learning systems. Sixthly, when students believe that the e-learning system is of practical use to improve their academic performance, this perceived usefulness directly and profoundly affects their behavioral intention, making them more willing to adopt and use the system actively. Thus, perceived usefulness not only directly affects students' behavioral intention but also indirectly affects their use behavior of e-learning systems by shaping their attitude and acceptance of the system. Overall, the behavioral intention of students to use e-learning systems has a profound impact. According to the research of Samsudeen and Mohamed (2019), the elements of the UTAUT2 model play a significant and key role in students' behavioral intention and actual use behavior of the e-learning system. Their study revealed the criticality of behavioral intentions in shaping student use behavior in e-learning systems. This means that the willingness and expectations of students regarding the use of e-learning systems directly shape their ultimate actual use behavior.

Therefore, the study aimed to gain insight into the important influencing factors of subjective norms, effort expectations, Internet experience, e-learning motivation, perceived usefulness, and behavioral intentions in e-learning system use behaviors of college students in Henan Vocational Institute of Arts, China.

5.2 Recommendation

The use behavior of students in e-learning systems at Henan Vocational Institute of Arts is influenced by various factors, including subjective norms, effort expectancy, Internet experience, e-learning motivation, and perceived usefulness. Firstly, in the learning environment, individuals' perceptions of others' expectations and social pressure play a crucial role in students' behavioral intentions. Students often shape their learning behavioral intentions based on subjective norms considered important or socially acceptable. Secondly, students' effort expectations towards technology use are a key factor in determining their behavioral intentions and actual technological usage. Thirdly, students using the internet more frequently and for longer durations are likelier to adopt e-learning systems. The level of student motivation not only relates to their interest in e-learning but significantly influences their active participation and full engagement in e-learning.

The research emphasizes the influence of subjective norms on students' formation of positive behavioral intentions within -learning systems. Furthermore, students' perceived usefulness of e-learning systems directly or indirectly affects their attitudes and acceptance levels, influencing their intentions to adopt their e-learning systems. Ultimately, students' behavioral intentions towards e-learning systems have a profound impact on the actual use of e-learning systems, as their intentions and expectations directly shape their use behaviors in applying the e-learning systems.

In summary, this study emphasizes the key factors influencing students' use behavior in e-learning systems, including subjective norms, effort expectancy, Internet experience, e-learning motivation, perceived usefulness, and behavioral intention. These research findings hold crucial significance for designing and promoting e-learning systems to enhance successful adoption and effective utilization. These discoveries contribute to better meeting student needs, improving user experience, and fostering active engagement and full utilization of e-learning systems. Overall, these research results provide valuable guidance for formulating strategies to enhance the adoption and effective use of e-learning systems.

5.3 Limitation and Further Study

When delving into the discussion of the limitations of this study and future research recommendations, it is necessary to consider various aspects of expansion in detail. Firstly, the specificity of the study's sample is emphasized, and it is suggested that future research broaden the sample scope to include students from different regions and institutions to enhance the universality of the results. Secondly, recommendations are made regarding the impact of cultural differences, encouraging global cross-cultural comparisons to understand better how different cultures influence the behavior of e-learning systems. Additionally, the potential subjective bias in relying on student self-reports is pointed out, and future research is advised to employ various methods for objective assessment.

Furthermore, criticism is raised about the neglect of time factors, and it is suggested that long-term tracking studies be conducted to reveal the influence of time factors on students' use behavior. When considering the complex relationships between variables, emphasis is placed on in-depth research into these interactions, possibly explaining them through statistical methods or model analysis. Regarding subjective norms and effort expectations, the importance of studying intervention measures is emphasized to provide practical suggestions for educational applications. Encouragement is given for broader research in different cultural backgrounds to comprehensively understand the impact of culture on the use behavior of e-learning systems.

Suggestions are made to consider the technical-specific factors of different e-learning systems to meet students' needs better. Advocacy for long-term tracking studies is made to better understand student changes at different time points. Finally, a strong emphasis is placed on in-depth analysis of factors such as perceived usefulness and learning motivation to understand better students' reactions and decision-making processes regarding e-learning systems.

In future research, these recommendations will contribute to a more comprehensive understanding of students' use behavior in e-learning systems, providing targeted suggestions for designing more effective educational technologies and policies.

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