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

Influential Factors on English E-Learning Behavioral Intention and Usage Among Undergraduates at Chengdu University, Sichuan, China

Shuhui Wang*

Received: March 7, 2024. Revised: July 22, 2024. Accepted: Frebuary 18, 2025.

Abstract

Purpose: The research investigates factors impacting the E-learning Behavioral Intention and Use behavior of undergraduates in non-English majors of Chengdu University who represent the undergraduates of Sichuan Province in China. **Research design, data, and methodology:** 496 sample data from the target group was gathered using a questionnaire and the quantitative approach. After the index of item-objective congruence (IOC), and Cronbach's Alpha, the Confirmatory factor analysis (CFA) was applied to test the data to verify the causal link between the variables and the model's goodness of fit. Finally, the Structural Equation Model (SEM) was again applied to conclude the impact strength of each variable. **Results:** All six hypotheses are supported at the p-value ranging from, showing a significant impact. The impact strengths of the factors are in the order of behavioral intention to use behavior, hedonic motivation to behavioral intention, self- efficacy to behavioral intention, effort expectancy to behavioral intention, facilitating conditions to use behavior, and performance expectancy to behavioral intention. **Conclusions:** In order to spread English E-learning among undergraduates in China, governments, university administrators, and English E-learning cooperating companies should pay full attention to the impacting factors investigated in this research and follow up policies and measurements to create a comfortable English E-learning setting.

Keywords : Hedonic Motivation, Self- efficacy, Facilitating Conditions, Behavioral Intention, Use Behavior

JEL Classification Code: E44, F31, F37, G15

1. Introduction

Retrospectively, the development of e-learning in China has four stages. The first stage is the audio-visual teaching stage. At the beginning of the birth of information teaching, Audio-visual Teaching (AT) was mostly carried out in large cities in the form of slides, recordings, and films. The second stage is the computer-assisted Teaching (CAT) stage. The development of computers promoted the application of CAT experiments. Stage three is the Network Teaching (NT) stage, during which the multimedia network system with network and computer are regarded as the core parts and become more mature and widely used in teaching (Samsudeen & Mohamed, 2019). Now, Chinese education is in the fourth Intelligent Teaching (IT) stage. The development of intelligent technology opened the talent training mode and education and teaching reform in the new era.

There is a huge demand for English E-learning in China, as The Ministry of Education of China issued the College English Curriculum Requirements (CECR), which required that the single educational mode dominated by teacher teaching should be improved, all universities should fully utilize modern information technology, and classroom and computer-based English education should be implemented. The proposal of CECR is essential for the rapid improvement of IT and e-tech, which represented a development trend of English teaching and learning in the era and triggered a major E-learning reform in foreign language teaching and learning in Chinese universities.

There is a curriculum-compulsive force for undergraduates to learn English online, which makes studies in the way of English E-learning extremely urgent. English

1*Shuhui Wang, School of Foreign Languages and Culture, Chengdu University, Sichuan, China. Email: cdsophie@163.com

learning is vital for students in universities. College English, a compulsory course, lasts for the first two years of students' university careers (first- and second-year students). During these two years, students have the chance to use English E-learning. There are 16 credits for the course at Chengdu University.

2. Literature Review

2.1 Performance Expectancy

Performance Expectancy (PE) is the utility obtained from using a particular service, such as time, money, effort savings, convenience of payment, rapid recovery, and service efficacy (Tarhini et al., 2016). PE, in other words, gauged the degree to which an individual considers that using a service will enable him or her to profit from a banking job. Thongsri et al. (2018) define PE as the extent to which a person believes that adopting these technologies will enable him or her to accomplish his or her goals. Samsudeen and Mohamed (2019) measure PE as the extent to which a person believes that adopting a particular information system will improve his or her ability to do his or her job. As to the feature, Tarhini et al. (2017) state that the degree to which individuals feel utilizing a particular technology is commonplace for them and will enhance their performance is known as PE. It describes how strongly a person feels using E-learning would enhance academic achievement. PE, which refers to the academician's view that E-learning will allow them to do their job tasks more effectively and efficiently, is described in the study by Gunasinghe et al. (2020) as the user's belief that the target technology will improve his or her performance for work-related advantages.
H1: Performance expectancy has a significant impact on behavioral intention.

2.2 Effort Expectancy

Effort Expectancy (EE) is the amount to which a person feels he or she can utilize a technology without further effort. It represents the ease with which consumers can apply a technology (Samsudeen & Mohamed, 2019). Considering that E-learning is still in its developmental phase, EE is regarded as one of the most influential aspects in determining users' Behavioural Intention (BHI) to utilize the system. Gunasinghe et al. (2020) said that EE is the idea that a person's contact with a specific technology is problem-free. In the context of this research, EE refers to the academics' perception that E-learning is simple to handle. Prior research indicated that EE significantly affects the selection of BHI to use and actual technology usage (Thongsri et al., 2018). It is reinforced by the study's conclusion that EE has a major effect on BHI since applications requiring substantial effort to use would dissuade users from adopting it (Chua et al., 2018). If students have discovered that now E-learning is an easy-to-use and learn-with system, they would assume that it can assist them in achieving their learning objectives. Thus, Universities should consider this element when designing and changing E-learning, which makes it as easy to use as feasible (requiring less work) to encourage student adoption (Abbad, 2021). Subsequently, a hypothesis is derived:
H2: Effort expectancy has a significant impact on behavior intention.

2.3 Hedonic Motivation

Hedonic Motivation (HM) is described by Tarhini et al. (2017) as the method used to measure the user's user satisfaction and perceived entertainment. The hedonic incentive was introduced to their new model to incorporate the function of intrinsic utilities. The significance of HM originates from the novelty-seeking and inventiveness inherent in using new systems. Mittal et al. (2022) defined it as "an internal type of motivation that may include enjoyment, amusement, or pleasure obtained from utilizing any technology." HM is an internal motivator that indicates the extent to which information technology use results in pleasure (IT). Similar to how EE, UB, and FC are significant predictors of academicians' BHI to use e-learning, HM impacts academicians' BHI to use e-learning (Gunasinghe et al., 2020). Based on the self-determination theory, it is hypothesized that individuals will be intrinsically driven to engage in E-learning if they are interested in utilizing it. Mikalef et al. (2016) pointed out learners perceive that they will benefit from a certain E-learning, they will actively attempt to embrace and institutionalize it to improve their knowledge and abilities.

Consequently, HM influences HBI's use of e-learning technologies. Prior research has determined that HM has a crucial role in affecting the BHI of technology users, particularly in e-learning (Samsudeen & Mohamed, 2019). Therefore, when E-learning makes consumers happy, they are more likely to utilize it. HM has a good and substantial impact on students' BHI to utilize E-learning technologies. Subsequently, a hypothesis is derived:
H3: Hedonic motivation has a significant impact on behavioral intention.

2.4 Self-Efficacy

Scholars defined Self-efficacy (SE) as an individual's perception of computer skills as part of IT usage. SE is described in IT as "an individual's views about his or her ability to utilize computers to complete a job, rather than simple component abilities" (Compeau & Higgins, 1995).

SE impacts judgments over which behavior to adopt and the associated effort and persistence. It can be a source of self-motivation (Kankanhalli et al., 2005). Zhang et al. (2012) indicated that SE refers to a person's confidence during his or her capacity to accomplish the activity. It does not indicate a person's real skills and abilities but acts as a type of self-evaluation of their potential. A greater degree of SE increases an individual's propensity to engage in a particular behavior. SE relates specifically to students' confidence in providing important knowledge in a discussion format. In the context of e-learning technology, McFarland (2001) verified that SE in computer technology directly impacts e-learning utilization, usefulness, ease of use, and perceived utility. According to Lam et al. (2007), the most influential factor on hotel workers' BHI regarding implementing information technology was SE (IT). Subsequently, a hypothesis is derived:

H4: Self-efficacy has a significant impact on behavioral intention.

2.5 Behavioral Intention

Four elements, namely organizational support, individual acceptance, societal beliefs, and the quality and dependability of the information technology system, significantly impact the Behavioral Intention (BHI) of students who actively utilize (ACT) technology (Tandon et al., 2021). Chua et al. (2018) described BHI as an individual's willingness and purpose to engage in a specific behavior. According to the model results, the assumption demonstrating the beneficial effect of BHI had not been supported, the link between BHI and Use Behaviour (UB) diverges (Twum et al., 2021). Chua et al. (2018) determines technological acceptability. Therefore, the acceptance of E-learning is a strong indicator of the BHI within the E-learning context. BHI is the measure of the likelihood that the behavior will be performed, which leads to use intention. Subsequently, a hypothesis is derived:

H5: Behavioral intention has a significant impact on use behavior.

2.6 Facilitating Conditions

UTAUT also hypothesizes that Facilitating Conditions (FC) directly affect UB; UB comprises behavioral control, FC, and compatibility (Maldonado et al., 2011). Samsudeen and Mohamed (2019) stated that FC is the physical location or environmental variables that persuade a person to engage in certain behaviors. It is an ambient component that influences an individual's perception of a task's difficulty or ease. It is the external resources required to assist the execution of a specific behavior. As defined by Gunasinghe et al. (2020), FC refers to the user's perception that infrastructure and equipment are readily available to facilitate the application of targeted technology. Abdou and Jasimuddin (2020) discovered that FC impacts BHI to utilize E-learning systems. FC may comprise assistance, knowledge, and E-learning, leading to the appearance, training, etc., that might impact a student's desire to utilize E-learning, according to Twum et al. (2021). Subsequently, a hypothesis is derived:

H6: Facilitating conditions has a significant impact on use behavior.

2.7 Use Behavior

The intensity of users' use of a technology is known as Use behavior (UB) (Awwad & Al-Majali, 2015). Chua et al. (2018) frequently calculate UB using actual frequency data from technology use. Many different models of technology adoption have been proposed to describe how people use technology. It is so because UB is the best at determining how people use a given technology. Additionally, the effect on UB done by BHI is significant and positive in the TPB, TAM, and DTPB models. According to Taylor and Todd (1995), a person's prior technology use will likely result in higher BHI and a stronger UB of technology. Williams et al. (2015) have shown that numerous technology adoption models have been created to describe how people use technology because consumer UB is the best indicator of actual technology usage. Tarhini et al. (2016) highlighted the significance of the connection between BHI and UB for E-learning.

3. Research Methods and Materials

3.1 Research Framework

There are three theoretical frameworks listed in detail as follows.

Based on UTAUT, Tandon et al. (2021) determined the facilitators and obstacles in the acceptance of e-learning among architecture undergraduate students. Five constructs are described as inhibitors, and nine are recognized as facilitators. A systematic questionnaire received responses from 596 undergraduate architecture students.

Tarhini et al. (2017) explored the main variables influencing or impeding the acceptance of the e-learning system in the UK. UTAUT2 created the conceptual framework by adding two more components -- trust and Self-efficacy (SE).

The major goal of Samsudeen and Mohamed's (2019) study was to look at significant elements that can favor or hinder undergraduates and graduate students located in 15 public schools in Sri Lanka from adopting or using E-learning technologies consistently. Sri Lankans were perceived as having high-power distance, feminine values, and collectivism in their culture.

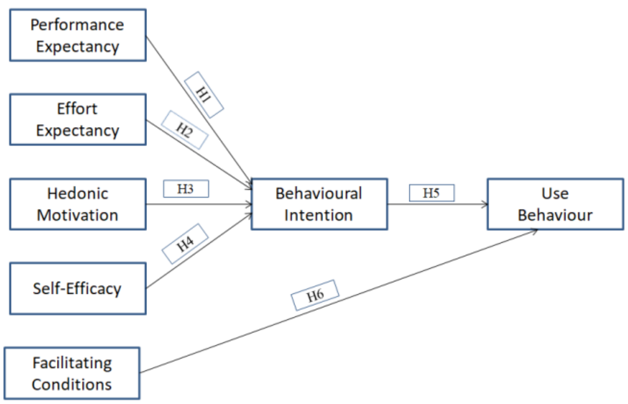

Figure 1: Conceptual Framework

H1: Performance expectancy has a significant impact on behavioral intention.
H2: Effort expectancy has a significant impact on behavior intention.
H3: Hedonic motivation has a significant impact on behavioral intention.
H4: Self-efficacy has a significant impact on behavioral intention.
H5: Behavioral intention has a significant impact on use behavior.
H6: Facilitating conditions has a significant impact on use behavior.

3.2 Research Methodology

Survey questionnaires needed to be employed to gather quantitative research data (Chen & Hirschheim, 2004). Students of higher education in China should not employ qualitative research since it is difficult to generalize from such studies (Hennink et al., 2020), which means that a quantitative research method is significantly more appropriate for studies on Chinese students enrolled in higher education than a qualitative one.

Prior to full-scale implementation, assessments were conducted to gauge the item-objective congruence (IOC) index through expert ratings, alongside a pilot test gathering 50 responses. The IOC results achieved a passing threshold of 0.6. Additionally, the questionnaire's validity and reliability were evaluated utilizing the Cronbach's Alpha approach, yielding a score of 0.7 or higher (Nunnally & Bernstein, 1994). Subsequent to reliability testing, statistical software was employed to analyze 496 accepted responses.

The researcher used a survey in the current investigation by giving the questionnaire to the participants in the unit. The respondents must answer every item on a self-administrative survey or independently. Then SEM executed the statistical testing and hypotheses verifying in statistical software makes the results precise and the analyses scientific.

3.3 Population and Sample Size

The target population was identified by Johnson and Christensen (2020) as an unconnected group of people who might be distinguished by the shared goal or intent to gather and analyze information in a quantitative research area. Saunders et al. (2016) stated that the target population was regarded as the study's dominating population and was thus also a component of the general population.

The target populations are the undergraduates of Chengdu University, a public university and a typical comprehensive school with more than ten discipline categories and 69 majors, of which there were more than 27,000 undergraduates covering first- and second-year students of non-English majors in Chengdu University.

3.4 Sampling Technique

Ogula (2005) predicted that a sampling method was a process or technique for choosing a sub-group from a certain population in a quantitative or qualitative study; it is the first stage before selecting a sizable number of people for a particular study. According to Sullivan et al. (2012), the study subject determines the sampling strategy, and the researcher may combine multiple sampling procedures.

This study uses Judgment and quota sampling as two stages to identify Chengdu University undergraduates. Thanks to this selection criterion, the samples might reflect the whole geographic region of Chengdu, Sichuan. Additionally, to exclude target respondents with more than a year of experience with English E-learning, the author sent questionnaires with screening questions.

Halabí and More-Espuivel (2017) stated that the minimal sample size required for structural equation modeling should be 100 people. Kline (2016) states that 375 samples are required as a minimum for SEM. With seven latent variables investigated and 29 scale items required, the minimum sample size calculated by the Daniel Soper calculator is suggested to be 425. Hence, the number of 450 samples for the target population is finally determined in the research.

Table 1: Sample Units and Sample Size

Four Main Majors (Non-English Majors)	Grades	Population Size	Proportional Sample Size
Computer Science	Freshmen	445	72
	Sophomore	432	70
Food and	Freshmen	503	81

Four Main Majors (Non-English Majors)	Grades	Population Size	Proportional Sample Size
Biological Engineering	Sophomore	461	74
Education	Freshmen	304	49
	Sophomore	282	45
Tourism and Culture Industry	Freshmen	186	30
	Sophomore	179	29
Total		**2792**	**450**

Source: Constructed by author

4. Results and Discussion

4.1 Demographic Information

Questionnaire delivery and collection were held during September and October 2023. Five hundred questionnaires were delivered, 497 samples were collected, and 496 were available.

Table 2 illustrates the characteristics of the demographic, who are first- and second-year students of non-English majors.

Table 2: Demographic Profile

Demographic and General Data (N=496)			Frequency	Percentage
Gender	Male		214	43%
	Female		282	57%
Majors and Year of Study	Computer Science	Freshmen	73	15%
		Sophomore	72	14%
	Food and Biological Engineering	Freshmen	82	17%
		Sophomore	75	15%
	Education	Freshmen	54	11%
		Sophomore	51	10%
	Tourism and Culture Industry	Freshmen	33	7%
		Sophomore	56	11%
Devices Used	by phone		306	62%
	by computer		158	32%
	by phone and computer		32	6%

4.2 Confirmatory Factor Analysis (CFA)

Lewis et al. (1995) used the statistical research method of confirmatory factor analysis (CFA) to estimate the mutual features among the variables for their hypothesis. According to Allen et al. (2009), the model of measurement, also known as CFA, was a method for figuring out how a group of indicators varied from one another. There is no need to be modified; all the practical values for Goodness of Fit are performing well with relevantly high standards.

According to Hulland (1999), the Factor loading value should be more than 0.5. As shown in Table 5, the data for it range from 0.730 to 0.850, which means excellent results. The two figures suit the standards for CR, which is required for above 0.7, and for AVE, which is asked for more than 0.5 (Bagozzi & Yi, 1988). Naturally, the data for Discriminant Validity is also confirmed.

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
Performance Expectancy (PE)	Tarhini et al. (2016)	4	0.875	0.971-0.806	0.875	0.635
Effort Expectancy (EE)	Samsudeen and Mohamed (2019)	4	0.867	0.779-0.801	0.870	0.625
Hedonic Motivation (HM)	Tarhini et al. (2017)	3	0.836	0.776-0.827	0.837	0.631
Self-Efficacy (SE)	Compeau and Higgins (1995).	4	0.867	0.754-0.817	0.868	0.622
Facilitating Conditions (FC)	Samsudeen and Mohamed (2019)	5	0.885	0.754-0.808	0.886	0.608
Behavioural Intention (BHI)	Tandon et al. (2021)	5	0.870	0.738-0.792	0.870	0.573
Use Behaviour (UB)	Chua et al. (2018)	4	0.875	0.754-0.801	0.864	0.613

To guarantee the robustness of the research, an examination was conducted on the square root of the extracted average variance, ensuring that all correlations surpass the respective values for each variable, as outlined in Table 4. In conducting Confirmatory Factor Analysis (CFA), various fit indices, including 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	< 3.00 (Hair et al., 2010)	1.384
GFI	≥ 0.80 (Kafetsios et al., 2011)	0.937
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.923
RMSEA	< 0.08 (Pedroso et al., 2016)	0.028
CFI	≥ 0.90 (Bentler, 1990)	0.981
NFI	≥ 0.90 (Hair et al., 2006)	0.936
TLI	≥ 0.90 (Hair et al., 2006)	0.979
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, RMSEA = root mean square error of approximation, NFI = normalized fit index, CFI = comparative fit index and TLI = Tucker Lewis index

The findings of this study, outlined in Table 5, indicate that both convergent and discriminant validity surpass the acceptable thresholds. Consequently, the study successfully establishes convergent and discriminant validity. Moreover, these measurement results affirm discriminant validity and validate the estimation of subsequent structural models.

Table 5: Discriminant Validity

	PE	EE	HM	SE	FC	BHI	UB
PE	**0.797**						
EE	0.302	**0.791**					
HM	0.244	0.286	**0.794**				
SE	0.186	0.251	0.204	**0.789**			
FC	0.280	0.335	0.237	0.332	**0.780**		
BHI	0.243	0.320	0.312	0.302	0.348	**0.757**	
UB	0.295	0.294	0.306	0.255	0.283	0.378	**0.783**

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 applied to analyze the collected data. SEM performs better than other techniques because it is integrative in many standard measurements, including correlation, multiple-regression, and factors-effects, into one single software (Lowry & Gaskin, 2014). At the 0.05 ($p > 0.05$) criterion, the ChiSquare (CMIN/DF) would yield an inconsequential result and a satisfactory fit of the model (Barrett, 2007). According to Blunch (2013), the GFI ranges from 0 to 1. Meanwhile, Kafetsios et al. (2011) pointed out that it is acceptable when GFI is more than 0.8. As Sica and Ghisi (2007) recommended, a value of 0.80 or above is suitable for GFI and AGFI. In addition, the model fit should be at the level where the RMSEA is less than 0.05 (Browne & Cudeck, 1993). Hair et al. (2006) have verified that the optimal level for the model fit is 0.90, which means that the CFI threshold should be equal to or greater than 0.90. Hair et al. (2006) said that the optimal degree of the fit level that the researcher has incorporated into the indices for the present academic study, similar to CFI, should be either greater than or equal to 0.90 for NFI. Hair et al. (2006) TLI is between 0 and 1, where 1 indicates a perfect match. The appropriate degree for the TLI threshold should be larger than or equal to 0.90.

Table 6: Goodness of Fit for Structural Model

Fit Index	Acceptable Criteria	Statistical Values Before Adjustment	Statistical Values After Adjustment
CMIN/DF	< 3.00 (Hair et al., 2010)	2.199	2.138
GFI	≥ 0.80 (Kafetsios et al., 2011)	0.890	0.893
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.871	0.874
RMSEA	< 0.08 (Pedroso et al., 2016)	0.049	0.048
CFI	≥ 0.90 (Bentler, 1990)	0.939	0.954
NFI	≥ 0.90 (Hair et al., 2006)	0.894	0.898
TLI	≥ 0.90 (Hair et al., 2006)	0.933	0.936
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, RMSEA = root mean square error of approximation, NFI = normalized fit index, CFI = comparative fit index and TLI = Tucker Lewis index

4.4 Research Hypothesis Testing Result

The results show that all the hypotheses are supported by the P value ranging from < 0.001 to < 0.01, with the factors' impact strength in the order of BHI to UB (β=0.387, P< 0.001), HM to BHI (β=0.256, P< 0.001), SE to BHI (β=0.237, P< 0.001), EE to BHI (β=0.223, P< 0.001), FC to UB (β=0.187, P< 0.001), and PE to BHI (β=0.130, P=0.007).

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-value	Result
H1: PE→BHI	0.130	2.691**	Supported
H2: EE→BHI	0.223	4.477***	Supported
H3: HM→BHI	0.256	5.008***	Supported
H4: SE→BHI	0.237	4.734***	Supported
H5: BHI→UB	0.387	7.270***	Supported
H6: FC→UB	0.187	3.819***	Supported

Note: *** p<0.001, ** p<0.01
Source: Created by the author

In terms of factors impacting Behavioral Intention (BHI), Hedonic Motivation (HM) has the highest significant directed effect on BHI with β=0.256 and $p < 0.001$, showing as the strongest variable effect of English E-learning in the population of non-English majors' BHI, which is similar as previous researches done by (Samsudeen & Mohamed, 2019; Tandon et al., 2021; Twum et al., 2021). Hence, H3 is confirmed.

Considering the reliability of each item of Hedonic Motivation ranged at 0.700 (HM1=0.755, HM2=0.784, and HM3=0.779), which are all on the level of good but lower than the items of other variables, making the highest factor total effect of Hedonic Motivation not as high up distinguished as it is in other researches. This result implies that a small proportion of Chinese undergraduates of non-English majors are reluctant to recognize and exhibit their favor of English E-learning, even though the reaction would not obstruct Hedonic Motivation being the baseline and the most impactful factor on Behavioral Intention on applying English E-learning in this research.

Then it is followed by Self-efficacy (SE) (β=0.237, $p < 0.001$) and Effort Expectancy (EE) (β=0.223, $p < 0.001$), indicating that non-English first- and second-year students have the confidence in using English E-learning and find learning English online easy, which have already been proved by (Ali et al., 2018; Chandio et al., 2013; Zimmerman & Kitsantas, 1999) on Self-efficacy and (Samsudeen & Mohamed, 2019; Tandon et al., 2021; Tarhini et al., 2017) on the effect of Effort Expectancy. Hence, both H4 and H2 are both confirmed.

It is not surprising to see Self-Efficacy and Effort Expectancy having similar factor effects on behavioral Intention in English E-learning because the two variables are both the ones inflecting individual inner cognition and certainty on the technology of English E-learning. Self-efficacy and Effort Expectancy is located on the secondary rank among the five factors investigated because 61% of the participant samples majoring in Science and Engineering possess skillful computer techniques, which makes them confident in English E-learning operation and feel learning English online easy in various aspects.

Performance Expectancy (PE) impacts significantly on behavioral Intention; however, it is less impactful with the lowest factor loading (β=0.130, $p < 0.007$) compared to the other three factors. This finding is consistent with previous research (Mikalef et al., 2016; Mittal et al., 2022; Tarhini et al., 2017), where Performance Expectancy is a significant driving force impacting the behavioral Intention of English E-learning. Hence, H1 is confirmed.

Performance Expectancy has the lowest impactful factor effect on Behavioral Intention among undergraduates in non-English Majors because the participant samples, especially the ones majoring in computer science, are so familiar with E-learning and so sophisticated in computer skills that they have less expectancy of getting delighted performance through efforts. Compared with the ones majoring in English, who are less skillful in E-learning than undergraduates in non-English Majors, the Performance Expectancy factor effect performs up to β=0.255 with $p < 0.001$. It can be suggested that the more skillful the learners are in English E-learning, the less significant the impact of behavioral intention performance expectancy.

5. Conclusion and Recommendation

5.1 Conclusion and Discussion

This research investigated the factors influencing the E-learning Behavioral Intention and Use behavior among undergraduates majoring in non-English subjects at Chengdu University, representing Sichuan Province in China. The study employed a quantitative approach and gathered data from a sample of 500 participants through a questionnaire. The data underwent rigorous testing, including the examination of the item-objective congruence (IOC), Cronbach's Alpha for reliability, Confirmatory Factor Analysis (CFA) to verify causal links between variables, and Structural Equation Model (SEM) to determine impact strengths.

The study found significant support for all six hypotheses, with p-values indicating a significant impact. The impact strengths of the factors were ranked as follows: behavioral intention to use behavior, hedonic motivation to behavioral intention, self-efficacy to behavioral intention, effort expectancy to behavioral intention, facilitating conditions to use behavior, and performance expectancy to behavioral intention.

To promote English E-learning among undergraduates in China, it is imperative for governments, university administrators, and E-learning companies to prioritize the factors identified in this research. Strategies and policies should be developed to create a conducive environment for English E-learning. This includes enhancing self-efficacy and motivation among students, improving accessibility and ease of use of E-learning platforms, and providing necessary resources and support for successful E-learning implementation.

By addressing these factors and implementing targeted interventions, stakeholders can facilitate the adoption and utilization of English E-learning platforms among non-English major undergraduates in China. This, in turn, can contribute to the enhancement of English proficiency levels and academic success among students, thereby supporting broader educational and societal goals.

5.2 Recommendation

In recent years, the utilization of E-learning platforms has gained significant traction, particularly in higher education institutions worldwide. However, despite its potential to revolutionize learning experiences, the adoption of E-learning among non-English major undergraduates presents unique challenges and opportunities. This essay explores key recommendations and strategies to enhance E-learning adoption among this demographic, drawing insights from research conducted at Chengdu University in Sichuan Province, China.

The research investigated factors influencing E-learning Behavioral Intention and Use behavior among non-English major undergraduates, emphasizing the importance of addressing key factors to promote successful adoption.

Firstly, enhancing self-efficacy and motivation among students is crucial. Implementing programs and initiatives to boost students' confidence in their ability to engage with E-learning materials and fostering intrinsic motivation through rewards and recognition can significantly impact adoption rates.

Secondly, improving accessibility and usability of E-learning platforms is essential. Ensuring platforms are user-friendly, intuitive, and accessible across different devices and internet connections can facilitate seamless E-learning experiences, removing barriers to adoption.

Thirdly, providing comprehensive training and support to students is vital. Offering tutorials, workshops, and technical assistance can help familiarize students with E-learning tools and resources, empowering them to navigate platforms effectively and address any challenges they encounter.

Additionally, creating collaborative learning communities within E-learning platforms is essential. Encouraging students to engage in online forums, discussion groups, and peer-to-peer learning opportunities fosters a sense of community and collaboration, enhancing learning outcomes and adoption rates.

Furthermore, integrating E-learning components into the curriculum is critical. Designing interactive and engaging E-learning modules that complement traditional classroom teaching and align with course objectives can enhance student engagement and participation.

Moreover, promoting awareness and adoption of E-learning through targeted campaigns and initiatives is essential. Highlighting the benefits of E-learning and sharing success stories from students who have benefited from it can inspire others to embrace it as a valuable learning tool.

Collaborating with stakeholders, including government agencies, educational institutions, and E-learning companies, is also paramount. Developing policies, funding initiatives, and partnerships that support the expansion and enhancement of E-learning programs can create a more robust and sustainable E-learning ecosystem.

Finally, continuous monitoring and evaluation of E-learning initiatives are essential. Collecting feedback from students, instructors, and other stakeholders and using data analytics to track progress and measure the impact of E-learning on student outcomes allows for refinement and improvement over time.

In conclusion, enhancing E-learning adoption among non-English major undergraduates requires a multifaceted approach that addresses key factors influencing Behavioral Intention and Use behavior. By implementing the recommendations outlined above, stakeholders can promote the adoption and utilization of E-learning platforms, thereby enhancing English language proficiency, academic performance, and overall learning outcomes among non-English major undergraduates.

5.3 Limitation and Further Study

There are many limitations in the current research. Accordingly, further exploration should be scheduled.

Other factors, such as academic tenacity and faculty adviser influence, should be considered and included in the conceptual framework, making the framework more complementary and scientific.

A more detailed analysis should be carried out. For example, the analysis based on sample units divided into majors listed as Computer Science, Food and Biological Engineering, Education, and Tourism and Culture Industry should be compared. One of the results in further exploration is expected to display the distinguished gap in the factor effects of Performance Expectancy followed by Effort Expectancy and Self-efficacy, which are the factors that often interfere with online skills.

Data for English majors should be provided as a contrast for the undergraduates of non-English majors. The topic of the contrast should focus on the difference and the gap in individual factor effect strength, as well as the further reasons for it.

References

Abbad, M. M. M. (2021). Using the UTAUT model to understand students' usage of e-learning systems in developing countries. *Education and Information Technologies, 26,* 7205-7224. https://doi.org/10.1007/s10639-021-10573-5

Abdou, D., & Jasimuddin, S. M. (2020). The use of the UTAUT model in the adoption of E-learning technologies: an empirical study in France based banks. *Journal of Global Information Management. 4*(28), 38-51.
https://doi.org/10.4018/jgim.2020100103

Ali, M., Raza, S. A., Qazi, W., & Puah, C.-H. (2018). Assessing e-learning system in higher education institutes: Evidence from structural equation modelling. *Interactive Technology and Smart Education, 15*(1), 59-78. https://doi.org/10.1108/itse-02-2017-0012

Allen, M., Titsworth, S., & Hunt, S. K. (2009). *Quantitative Research Communication* (1st ed.). Sage Publications Inc.

Awwad, M. S., & Al-Majali, S. M. (2015). Electronic library services acceptance and use: An empirical validation of unified theory of acceptance and use of technology. *The Electronic Library, 33*(6), 1100-1120. https://doi.org/10.1108/el-03-2014-0057

Bagozzi, R. P., & Yi, Y. (1988). On the evaluation of structural equation models. *Journal of the Academy of Marketing Science, 16*(1), 74-94. https://doi.org/10.1007/bf02723327

Barrett, P. (2007). Structural equation modelling: Adjudging model fit. *Personality and Individual Differences, 42*(5), 815-824. https://doi.org/10.1016/j.paid.2006.09.018

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

Blunch, N. (2013). *Introduction to Structural Equation Modeling using IBM SPSS Statistics and AMOS* (2nd ed.). 55 City.

Browne, M. W., & Cudeck, R. (1993). Alternative ways of assessing model fit. In K. A. Bollen and J. S. Long (Eds.), *Testing structural equation models* (pp. 136-162). Sage.

Chandio, F. H., Abbasi, M. S., Nizamani, H. A., & Nizamani, Q. U. A. (2013). Online banking information systems acceptance: a structural equation modelling analysis. *International Journal of Business Information Systems, 12*(2), 177. https://doi.org/10.1504/ijbis.2013.052050

Chen, W., & Hirschheim, R. (2004). A paradigmatic and methodological examination of information systems research from 1991 to 2001. *Information Systems Journal, 14*(3), 197-235. https://doi.org/10.1111/j.1365-2575.2004.00173.x

Chua, P. Y., Rezaei, S., Gu, M.-L., Oh, Y., & Jambulingam, M. (2018). Elucidating social networking apps decisions: Performance expectancy, effort expectancy and social influence. *Nankai Business Review International, 9*(2), 118-142. https://doi.org/10.1108/nbri-01-2017-0003

Compeau, D. R., & Higgins, C. A. (1995). Computer Self-Efficacy: Development of a Measure and Initial Test. *MIS Quarterly, 19*(2), 189. https://doi.org/10.2307/249688

Gunasinghe, A., Hamid, A. J., Khatibi, A., & Azam, F. S. M. (2020). The adequacy of UTAUT-3 in interpreting academician's adoption to e-Learning in higher education environments. *Interactive Technology and Smart Education, 17*(1), 86-106. https://doi.org/10.1108/itse-05-2019-0020

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). *Multivariate data analysis* (7th ed.). Prentice-Hall.

Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E., & Tatham, R. L. (2006). *Multivariant Data Analysis* (6th ed.). Pearson International Edition.

Halabí, V., & More-Espuivel, R. (2017). Sample Sizes Using Structural Equation Modeling with Latent Variables: A Practical Method. *Act alidades Investigative en Educación, 17*(1), 1-34.

Hennink, M., Hutter, H., & Bailey, A. (2020). *Qualitative research methods* (2nd ed.). Sage Publications Ltd.

Hulland, J. (1999). Use Of Partial Least Squares (PLS) In Strategic Management Research: A Review of Four Recent Studies. *Strategic Management Journal, 20*(2), 195-204. https://doi.org/10.1002/(sici)1097-0266(199902)20:2<195::aid-smj13>3.3.co;2-z

Johnson, R. B., & Christensen, L. (2020). *Educational Research: Quantitative, Qualitative, and Mixed Approaches* (7th ed.). Sage.

Kafetsios, K., Nezlek, J. B., & Vassiou, A. (2011). A multilevel analysis of relationships between leaders' and subordinates' emotional intelligence and emotional outcomes. *Journal of Applied Social Psychology, 41*(5), 1121-1144.

Kankanhalli, A., Tan, B. C. Y., & Wei, K.-K. (2005). Contributing Knowledge to Electronic Knowledge Repositories: An Empirical Investigation. *MIS Quarterly, 29*(1), 113. https://doi.org/10.2307/25148670

Kline, R. B. (2016). *Principles and Practice of Structural Equation Modeling* (4th ed.). The Guilford Press.

Lam, T., Cho, V., & Qu, H. (2007). A study of hotel employee behavioral intentions towards adoption of information technology. *International Journal of Hospitality Management, 26*(1), 49-65. https://doi.org/10.1016/j.ijhm.2005.09.002

Lewis, B. R., Snyder, C. A., & Rainer, K. R. (1995). An empirical assessment of the Information Resources Management construct. *Journal of Management Information Systems, 12*(1), 199-223. https://doi.org/10.1080/07421222.1995.11518075

Lowry, P. B., & Gaskin, J. (2014). Partial Least Squares (PLS) Structural Equation Modeling (SEM) for Building and Testing Behavioral Causal Theory: When to Choose It and How to Use It. *IEEE Transactions on Professional Communication, 57*(2), 123-146. https://doi.org/10.1109/tpc.2014.2312452 https://doi.org/10.1109/TPC.2014.2312452

Maldonado, T. U. P., Khan, F. G., Moon, J., & Rho, J. J. (2011). E-learning motivation and educational portal acceptance in developing countries. *Online Information Review, 35*(1), 66-85. https://doi.org/10.1108/14684521111113597

McFarland, D. J. (2001). The role of age and efficacy on technology acceptance: implications for e-learning. *Proceedings of the World Conference on the WWW and Internet*, 2-7.

Mikalef, P., Pappas, I. O., & Giannakos, M. (2016). An integrative adoption model of video-based learning. *The International Journal of Information and Learning Technology, 33*(4), 219-235. https://doi.org/10.1108/ijilt-01-2016-0007

Mittal, A., Mantri, A., Tandon, U., & Dwivedi, Y. K. (2022). A unified perspective on the adoption of online teaching in higher education during the COVID-19 pandemic. *Information Discovery and Delivery, 50*(2), 117-132. https://doi.org/10.1108/idd-09-2020-0114

Nunnally, J. C., & Bernstein, I. H. (1994). *Psychometric theory* (3rd ed.). McGraw-Hill.

Ogula, P. A. (2005). *Research methods* (1st ed.). Cuea Publications.

Pedroso, R., Zanetello, L., Guimarães, L., Pettenon, M., Gonçalves, V., Scherer, J., Kessler, F., & Pechansky, F. (2016). Confirmatory factor analysis (CFA) of the Crack Use Relapse Scale (CURS). *Archives of Clinical Psychiatry (São Paulo), 43*(3), 37-40. https://doi.org/10.1590/0101-60830000000081

Samsudeen, N. S., & Mohamed, R. (2019). University students' intention to use e-learning systems: A study of higher educational institutions in Sri Lanka. *Interactive Technology and Smart Education, 3*(6), 219-238.

Saunders, M., Lewis, P., & Thornhill, A. (2016). *Research methods for business students* (7th ed.). Pearson

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

Sullivan, T. J., Priestley, M. J. N., & Calvi, G. M. (2012). *A Model Code for the Displacement-Based Seismic Design of Structures* (1st ed.). IUSS Press

Tandon, U., Mittal, A., Bhandari, H., & Bansa, K. (2021). E E-learning adoption by undergraduate architecture students: facilitators and inhibitors. *Engineering, Construction and Architectural Management, 29*(10), 4287-4312. https://doi.org/10.1108/ecam-05-2021-0376

Tarhini, A., El-Masri, M., Ali, M., & Serrano, A. (2016). Extending the UTAUT model to understand the customers' acceptance and use of internet banking in Lebanon: A structural equation modeling approach. *Information Technology & People, 29*(4), 830-849. https://doi.org/10.1108/itp-02-2014-0034

Tarhini, A., Masa'deh, R. E., Al-Busaidi, K. A., Mohammed, A. B., & 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, S., & Todd, P. (1995). Decomposition and Crossover Effects in the Theory of Planned Behavior: A Study of Consumer Adoption Intentions. *International Journal of Research in Marketing, 12*(2), 137-155. https://doi.org/10.1016/0167-8116(94)00019-k

Thongsri, N., Shen, L., Bao, Y., & Alharbi, I. M. (2018). Integrating UTAUT and UGT to explain behavioral intention to use M-learning: A developing country's perspective. *Journal of Systems and Information Technology, 20*(3), 278-297. https://doi.org/10.1108/jsit-11-2017-0107

Twum, K. K., Ofori, D., Keney, G., & Korang-Yeboah, B. (2021). Using the UTAUT, personal innovativeness and perceived financial cost to examine student's intention to use E-learning. *Journal of Science and Technology Policy Management, 13*(3), 713-737. https://doi.org/10.1108/jstpm-12-2020-0168

Williams, A. P., Seager, R., Abatzoglou, J. T., Cook, B. I., Smerdon, J. E., & Cook, E. R. (2015). Contribution of anthropogenic warming to California drought during 2012-2014. *Geophysical Research Letters, 42*(16), 6819-6828. https://doi.org/10.1002/2015gl064924

Zhang, Y., Fang, Y., Wei, K.-K., & Wang, Z. (2012). Promoting the intention of students to continue their participation in e-learning systems: The role of the communication environment. *Information Technology & People, 25*(4), 356-375. https://doi.org/10.1108/09593841211278776

Zimmerman, B. J., & Kitsantas, A. (1999). Acquiring writing revision skill: Shifting from process to outcome self-regulatory goals. *Journal of Educational Psychology, 91*(2), 241-250. https://doi.org/10.1037/0022-0663.91.2.241