pISSN: 1906 - 3296 © 2020 AU-GSB e-Journal.
eISSN: 2773 - 868x © 2021 AU-GSB e-Journal.
https://assumptionjournal.au.edu/index.php/AU-GSB

Decoding E-Learning Adoption: Key Drivers Shaping Students' Intentions in Shanghai's Higher Education Landscape

Li Lu*

Received: August 13, 2024. Revised: September 4, 2024. Accepted: February 22, 2025.

Abstract

Purpose This study explores how performance expectancy, effort expectancy, social influence, hedonic motivation, habit, facilitating conditions, and learning value affect the behavioral intention of university students in Shanghai to use e-learning. **Research design, data, and methodology:** The study's validity was ensured by using the Index of Item-Objective Congruence, and reliability was evaluated with Cronbach's Alpha. A total of 100 valid responses were analyzed through multiple linear regression. Additionally, 30 students took part in a 14-week Intervention Design Implementation (IDI), with results analyzed via a paired-sample t-test. **Results:** Data from 100 students were analyzed using multiple linear regression, revealing that performance expectancy, effort expectancy, facilitating conditions, hedonic motivation, habits, and learning value have a significant impact on behavioral intention. Nevertheless, social influence has no significant impact on behavioral intention. Additionally, there is a significant mean difference in performance expectancy, effort expectancy, facilitating conditions, hedonic motivation, habits, learning value, and behavioral intention between the Pre-IDI and Post-IDI stages. **Conclusions:** The findings reveal that all the factors studied impact behavioral intentions, providing valuable insights for improving e-learning platform design in higher education. This research offers a strong foundation for future studies in this area.

Keywords: Electronic Learning, Hedonic Motivation, Habit, Facilitating Conditions, Behavioral Intentions

JEL Classification Code: I23, J28, L2

1. Introduction

As technology and the internet evolve rapidly, blended learning has emerged as a preferred educational method in vocational nursing studies. This approach combines traditional classroom instruction with online learning, providing students with a diverse range of activities to enhance their understanding and skills. Blended learning offers numerous benefits, including increased flexibility and accessibility, personalized learning experiences, and improved student engagement and academic performance (Li & Li, 2018). However, the effectiveness of blended learning in vocational nursing education depends on careful design and implementation. It is essential to investigate the factors influencing student academic performance in this context to maximize its effectiveness (Kang & Kim, 2021). While previous research suggests that learning motivation, active participation, and constructive feedback positively correlate with student performance, their interplay within a blended learning environment remains largely unexplored (Gjestvang et al., 2021).

The early 21st century has seen an unprecedented integration of digital technology into educational practices, leading to the blended learning model—a pedagogical approach that merges traditional face-to-face instruction with online learning activities. This model has been widely adopted across various disciplines, including health sciences and nursing education. Globally, blended learning is praised for its flexibility, accessibility, and potential to enhance learning outcomes (Allen et al., 2007; Graham, 2006). In nursing education, this approach is especially relevant due to the profession's practical nature and the ongoing need for

1*Li Lu, Ph.D. Candidate, Educational Administration and Leadership, Assumption University, Thailand. E-mail: Molly20210801@126.com

professional development in response to rapid advancements in healthcare (Sharpe et al., 2006).

The effectiveness of blended learning in nursing education has become a focal point of educational research. International studies indicate that blended learning can enhance student engagement, satisfaction rates, and academic performance compared to traditional learning methods (Billings & Halstead, 2012). A meta-analysis by Means et al. (2013) found that students in blended learning environments often outperform those in fully online or face-to-face courses, suggesting a synergistic effect of combining both methods.

In China, the transition to blended learning in vocational education aligns with the country's educational reform goals, which emphasize innovative teaching methods and improved learning quality (Ministry of Education of the People's Republic of China, 2010). The Chinese government is committed to enhancing nursing education standards, which is crucial for addressing the healthcare needs of its growing and aging population (Zhang et al., 2008). In this context, blended learning serves not only as a pedagogical choice but also as a strategic educational policy aimed at strengthening the competencies of nursing professionals (Zhang et al., 2022).

Shanghai’s educational landscape is characterized by innovative teaching and learning approaches. The city’s strategic educational reform plan includes significant investments in educational technology and teacher training, aiming to create a more flexible and dynamic learning environment (Shanghai Municipal Education Commission, 2015). The integration of blended learning within nursing vocational education in Shanghai reflects these broader trends, positioning the city’s educational institutions as leaders in the field (Bi et al., 2014).

Consequently, the importance of this study lies in its potential to provide valuable insights into the factors influencing student performance in blended learning within the context of vocational nursing education in Shanghai. The findings from this study are expected to assist educators and curriculum designers in developing more engaging and effective blended learning courses for vocational nursing students. Ultimately, this could contribute to the cultivation of skilled and compassionate healthcare professionals.

The rapid advancement of information technology and the widespread adoption of the Internet have brought about significant changes in various aspects of life, particularly in global education (Vidakis & Charitakis, 2018). As a result, educational institutions have integrated new technologies into their teaching methods. E-learning has emerged as a widely used instructional approach, especially in higher education, and has been shown to improve teaching quality, reduce educational costs, and enhance student learning outcomes. Universities play a crucial role in developing online education curricula, significantly contributing to this field. In Shanghai, a key economic and educational center in China, the higher education sector has become a leading example. Despite the many benefits of e-learning, such as convenience, timeliness, and cost-effectiveness, students' willingness to adopt and fully participate in e-learning depends on various influencing factors.

This study is motivated by the limited research on the factors that influence students' intentions to adopt e-learning. Therefore, examining the factors affecting the intentions of higher education students in Shanghai to use e-learning is highly valuable. This research provides insights into students' attitudes and behaviors toward e-learning, offering a framework for universities to develop effective e-learning strategies.

2. Literature Review

2.1 Behavioral Intention

Behavioral intention serves as a crucial predictor of an individual's likely actions, reflecting their willingness and effort to engage in specific activities. It is commonly viewed as an early indicator of future behavior (Venkatesh et al., 2003). In academic research, especially in management studies, behavioral intention is often employed as a central factor in analyzing consumer decision-making processes. In this study, behavioral intention is treated as a dependent variable, highlighting its importance in predicting actual usage patterns.

2.2 Performance Expectancy

The concept of performance expectancy is rooted in the expectancy theory of motivation, which suggests that an individual's motivation is influenced by the expected outcomes, the attractiveness of those outcomes, and the belief in one's ability to carry out the necessary actions (Vroom, 1964). A review of studies in various educational technology contexts, such as digital libraries (Hamzat & Mabawonku, 2018), mobile learning (Ali & Arshad, 2018), and e-learning within data mining (Fernandez et al., 2014), consistently shows that performance expectations significantly influence the intention to use these technologies. This leads to the development of Hypothesis 1, as follows:

H1: Performance expectancy has a significant impact on behavior intention.

2.3 Effort Expectancy

Effort Expectancy, as defined by the Technology Acceptance Model (TAM), refers to the perceived ease of using a system (Davis et al., 1989). This factor is critical in determining users' willingness to adopt information technology, particularly in educational settings, where lower perceived effort typically results in quicker adoption. Empirical studies have shown that Effort Expectancy significantly impacts the intention to use learning systems (Tarhini et al., 2017). This study seeks to empirically confirm this theoretical relationship. Thus, Hypothesis 2 is formulated as follows:
H2: Effort expectancy has a significant impact on behavior intention.

2.4 Social Influence

Luarn et al. (2015) described social influence as a social condition, categorizing it into six types: subjective norms, information sharing, expressive power, relationship management, bond strength, and social support. Venkatesh et al. (2003) emphasized the significance of social influence in mandatory contexts, such as online learning platforms in educational institutions. In line with this, Ain et al. (2016) discovered that peers and teachers greatly influence Malaysian university students' use of mandatory Learning Management Systems (LMS). Consequently, Hypothesis 3 (H3) is proposed as follows:
H3: Social influence has a significant impact on behavior intention.

2.5 Hedonic Motivation

Hedonic motivation, rooted in the "hedonic theory of motivation" introduced by the British philosopher Bentham, posits that human behavior is driven by the desire for pleasure and the avoidance of pain. Chen and Wu (2017) found that hedonic motivation positively impacts students' intentions to use e-learning platforms, suggesting that enjoyment in e-learning encourages favorable attitudes and intentions toward its adoption. Similarly, Li and Li (2018) demonstrated that perceiving e-learning as enjoyable significantly influences university students' willingness to embrace educational technology in Shanghai. Therefore, Hypothesis 4 (H4) is formulated as follows:
Top of Form
Bottom of Form
H4: Hedonic motivation has a significant impact on behavior intention.

2.6 Habit

Venkatesh et al. (2012) define habit as a behavior that becomes automatic and occurs without conscious decision-making, often shaped by previous positive experiences with e-learning platforms. This suggests that regular use of e-learning can develop into a habit that influences long-term usage patterns (Verplanken & Wood, 2006). Oreg et al. (2011) further support this by showing that established habits in technology use significantly boost the intention to continue using e-learning systems. Consequently, Hypothesis 5 (H5) is presented as follows:
Top of FormBottom of Form
H5: Habit has a significant impact on behavior intention.

2.7 Facilitating Conditions

Venkatesh et al. (2003) define convenience in technology adoption as the availability of support and technical assistance for users, such as help desks and support menus. Zhang (2016) suggests that tailoring pedagogical methods to align with students' regulatory focuses and interests can significantly boost their motivation to engage with and learn from MOOCs. Additionally, Hu and Lai (2019) found that students' expectations and willingness to interact with learning management systems (LMS) on different devices are affected by their access to technical support and the necessary skills to use these systems. Therefore, Hypothesis 6 (H6) can be formulated as follows:Top of Form
Bottom of Form
H6: Facilitating conditions have a significant impact on behavior intention.

2.8 Learning Value

Ain et al. (2016) define Learning Value (LV) as the perceived benefits and overall worth that students associate with their e-learning experiences, taking into account the time and effort invested rather than the financial cost. The Technology Acceptance Model (TAM), developed by Venkatesh and Davis (2000), highlights perceived usefulness, which is closely linked to learning value. Sun and Zhang (2020) discovered that Chinese students are more inclined to engage with online platforms when they view the learning as valuable for gaining knowledge and enhancing their academic performance. Therefore, Hypothesis 7 (H7) is formulated as follows:
H7: Learning value has a significant impact on behavior intention.

3. Research Methods and Materials

3.1 Research Framework

The researcher utilized three theoretical models: the Technology Acceptance Model (Davis, 1989), the Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003), and the Theory of Planned Behavior (Ajzen, 1991). These theoretical frameworks supported and aided in the creation of the conceptual framework shown in Figure 1.

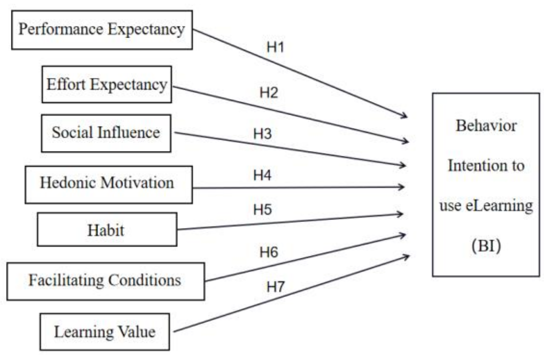

Figure 1: Conceptual Framework

H1: Performance expectancy has a significant impact on behavior intention.
H2: Effort expectancy has a significant impact on behavior intention.
H3: Social influence has a significant impact on behavior intention.
H4: Hedonic motivation has a significant impact on behavior intention.
H5: Habit has a significant impact on behavior intention.
H6: Facilitating conditions have a significant impact on behavior intention.
H7: Learning value has a significant impact on behavior intention.

3.2 Research Methodology

The research process was carried out in four stages. The first stage involved surveying the entire research population (n=105) to gather data for the conceptual framework. The hypotheses were then evaluated using multiple linear regression, retaining those with statistical significance (p-value < 0.05) while discarding the others. The second stage consisted of pre-IDI surveys conducted among the same 105 students. The third stage involved implementing the Intervention Design Implementation (IDI) with 30 participants from the Department of Education. In the final stage, the 30 participants completed post-IDI surveys, and the data collected were analyzed using paired-sample t-tests. This analysis allowed for a comprehensive evaluation of the research objectives and hypotheses by comparing the pre- and post-IDI results.

In conducting this study, ethical considerations were prioritized to ensure the protection of all participants. Informed consent was obtained from each participant prior to data collection, with detailed explanations provided regarding the study's purpose, procedures, and their rights.

3.3 Research Population, Sample Size, and Sampling Procedures

3.3.1 Research Population

The entire research group for the proposed conceptual framework consists of students from three of the 20 identified research directions: those majoring in animation, journalism, and education. All students have completed at least one semester at a university in Shanghai and have experience with online learning. A total of 105 students were selected for the study, with the Intervention Design Implementation Experimental Group consisting of 30 students from one of these disciplines.

3.3.2 Sample size

Determining the sample size depends on the selected analysis method; for example, Structural Equation Modeling (SEM) requires a larger sample size than statistical methods based on standard regression (Westland, 2010). The sample size is calculated using a small effect size (0.2), a probability level of 0.05, a conceptual model, and a questionnaire (defined below) with a sample size calculator for SEM research (Soper, 2020).

In regression analysis, many researchers recommend having at least ten observations for each variable (Hair et al., 2010). Therefore, the minimum sample size is calculated as follows:

Minimum sample size = 8 (number of variables in the Proposed Conceptual Framework) × 10 = 80 respondents.

As a result, the selected sample size is 105 respondents. Hair et al. (2010) suggests that a sample size ranging from 30 to 500 is sufficient for most research. In the preliminary diagnosis stage, the sample size for the reliability test is set at 15, while for multiple linear regression testing, it is 100. During the IDI stage, 30 students are chosen as participants for the IDI implementation. In the post-IDI stage, these same 30 students will serve as respondents for the research methods used in the pre-IDI stage.

3.3.3 Sampling Procedures

The researcher reached out to various groups of participants using the following sampling methods:

Sampling 1: Pilot Survey and Pilot Test
Thirty randomly chosen students were invited to participate in both the pilot survey and pilot test. They were asked to complete the survey questionnaire and offer feedback on their experience.

Sampling 2: Pre-survey
The pre-survey involved inviting 1,494 students from different academic years to complete printed survey questionnaires. After thorough review, 1,494 valid responses were confirmed.

Sampling 3: Sampling for IDI
For the IDI phase, 30 students were randomly selected and invited to participate.

3.4 Research Instruments

3.4.1 Design of Questionnaire

Questionnaire surveys provide questions and preset scales to the target population, forming the main raw data for further analysis (Hair et al., 2013). The survey questionnaire was generated using the Google Forms tool and sent offline to students at the selected university for preliminary data collection. Please ask the student union representative to help distribute the questionnaire randomly to college students until the given proportional sample size is reached.

3.4.2 Components of Questionnaire

The survey questionnaire consisted of two sections:

Part 1: Screening Questions

The initial section presents screening questions aimed at verifying respondents' eligibility for participation in the questionnaire survey. This study aims to investigate students who have been using e-learning for more than a year in universities in Shanghai.

Part 2: Factors influencing behavioral intention

The second section of the questionnaire determines factors influencing behavioral intention in using electronic learning with ratings ranging from disagreement to agreement on a five-point Likert scale.

3.4.3 IOC Results

The index of item-objective congruence (IOC) was employed in this study to assess validity. All items utilized a 5-point Likert scale. Respondents were instructed to mark their evaluations in the space provided below: a mark of "+1" indicates that the item aligns with measuring the construct and its objective; a mark of "0" suggests that the item is questionable in measuring the construct and its objective; and a mark of "-1" signifies that the item does not align with measuring the construct and its objective. Three experts were invited to provide IOC ratings for this study, consisting of one lecturer and two assistant professors from Assumption University. Items receiving a score below 0.67 needed to be reconsidered, while those with a score of 0.67 or higher could be retained (Carlson & da Silva, 2003).

3.4.4 Pilot survey and Pilot test results

The author performed a Confirmatory Analysis (CA) test on the top 30 respondents prior to distributing the questionnaire to a larger group. The dependent variable of behavioral intention yielded a value of 0.838. The results of the pilot test are presented in Table 3.6. The coefficient indicates that all constructs are acceptable and reliable, with an alpha value of 0.70 or higher. Consequently, the author proceeded to distribute the questionnaires to the target group until the sample size reached 100.

Table 1: Pilot Test Result

Variables	No. of Items	Sources	Cronbach 's Alpha	Strength of association
Performance Expectancy (PE)	4	Vroom (1964)	0.762	Acceptable
Effort Expectancy (EE)	4	Davis et al. (1989)	0.815	Good
Social Influence (SI)	4	Luarn et al. (2015)	0.742	Acceptable
Hedonic Motivation (HM)	4	Chen and Wu (2017)	0.728	Acceptable
Habit (HB)	4	Venkatesh et al. (2012)	0.811	Good
Facilitating Conditions (FC)	4	Venkatesh et al. (2003)	0.813	Good
Learning Value (LV)	4	Ain et al. (2016)	0.796	Acceptable

4. Results and Discussion

4.1 Results

4.1.1 Demographic Profile

The researcher presented the demographic profile of the entire research population (n=100), as illustrated in Table 2.

Table 2: Demographic Profile

Entire Research Population (n=100)		Frequency	Percent
Gender	Male	62	62%
	Female	38	38%
Age	18-25	83	83%
	26-33	10	56%
	34-41	5	5%
	42-49	2	2%
	Freshmen	12	12%

Entire Research Population (n=100)		Frequency	Percent
Year	Sophomores	25	25%
	Juniors	31	31%
	Seniors	31	31%
Total		**100**	**100%**
IDI Participants (n=30)		**Frequency**	**Percent**
Gender	Male	18	60%
	Female	12	20%
Age	18-25	21	70%
	26-33	6	20%
	34-41	2	6.7%
	42-49	1	3.3%
Year	Freshmen	5	16.7%
	Sophomores	10	33.3%
	Juniors	12	40%
	Seniors	3	10%
Total		**30**	**100%**

4.1.2 Results of multiple linear regression

The R-squared (R^2) value in a multiple linear regression model with seven independent variables explains 48.6% of the variability in behavioral intention.

Table 3: The multiple linear regression of five independent variables on behavior intention

Variables	Standard Coefficient 's Beta	T-Value	P-value	R	R Square
Performance Expectancy	0.471	7.708	0.000*	0.553	0.468
Effort Expectancy	0.375	3.824	0.001*		
Social Influence	0.205	7.237	0.089		
Hedonic Motivation	0.260	5.341	0.011*		
Habit	0.288	6.136	0.015*		
Facilitating Conditions	0.401	10.227	0.008*		
Learning Value	0.257	11.925	0.020*		

Note: p-value <0.05*

Multiple regression analysis conducted using SPSS indicated that all seven independent variables had a significant effect on the dependent variable, with p-values less than 0.05. The R-squared value of 0.468 implies that these variables account for approximately 46.8% of the variance in the dependent variable. All normalized regression coefficients were positive, indicating a positive relationship between the independent and dependent variables. The standardized regression coefficients revealed that performance expectancy, effort expectancy, social influence, hedonic motivation, habits, facilitating conditions, and learning value significantly impacted behavioral intention, as reflected by their respective coefficients (0.471, 0.375, 0.205, 0.260, 0.288, 0.257).

The following finalized research hypotheses pertain to the differences between pre- and post-IDI for most sub variables, except H3:

H8: There is a significant mean difference in Performance Expectancy between the Pre-IDI and Post-IDI stages.

H9: There is a significant mean difference in Effort Expectancy between the Pre-IDI and Post-IDI stages.

H10: There is a significant mean difference in Hedonic Motivation between the Pre-IDI and Post-IDI stages.

H11: There is a significant mean difference in Habit between the Pre-IDI and Post-IDI stages.

H12: There is a significant mean difference in Facilitating Conditions between the Pre-IDI and Post-IDI stages.

H13: There is a significant mean difference in Learning Value between the Pre-IDI and Post-IDI stages.

H14: There is a significant mean difference in Behavioral Intention between the Pre-IDI and Post-IDI stages.

4.2 IDI Intervention Stage

The complete development of the IDI phase lasts for a period of 14 weeks.

Table 4: IDI Activities

No.	Time and Duration	Implementation keywords
1	Week 1	Team establishment
		Goal setting
		SWOT diagnostic analytic tool
2	Week 2-4	Group mentoring
3	Week 5-8	Practical courses
4	Week 9-12	Individual counseling
5	Week 13-14	Interview and summary

4.3 Results Comparison between Pre-IDI and Post-IDI

A paired-sample t-test analysis was performed on all seven variables to determine if there were differences in behavioral intentions regarding the use of e-learning between the pre-IDI and post-IDI phases. The following tables present the results of the paired-sample t-test analysis for the seven variables under consideration:

Table 5: Paired-Sample T-Test Results

Variables	Mean	SD	SE	p-value
Performance Expectancy				
Pre-IDI	2.18	0.473	0.0863	p<0.01
Post-IDI	3.32	0.412	0.0752	
Effort Expectancy				
Pre-IDI	3.54	0.435	0.0792	p<0.01
Post-IDI	4.33	0.221	0.0403	
Hedonic Motivation				
Pre-IDI	3.27	0.461	0.0842	p<0.01
Post-IDI	4.08	0.382	0.0697	
Habit				
Pre-IDI	4.00	0.357	0.0652	p<0.01
Post-IDI	4.55	0.213	0.0389	
Facilitating Conditions				
Pre-IDI	3.69	0.377	0.0688	p<0.01
Post-IDI	4.43	0.289	0.0528	
Learning Value				
Pre-IDI	3.28	0.449	0.0820	p<0.01
Post-IDI	4.21	0.256	0.0467	
Behavior intention				
Pre-IDI	3.23	0.335	0.0612	p<0.01
Post-IDI	4.31	0.212	0.0387	

Table 5 displays the results of the paired-sample t-test comparing pre-IDI and post-IDI phases. Significant increases were noted in all factors:

Performance Expectancy: Increased from M=2.18, SD=0.473 to M=3.32, SD=0.412 (mean difference = 1.14, $p<0.001$), supporting H8.

Effort Expectancy: Increased from M=3.54, SD=0.435 to M=4.33, SD=0.221 (mean difference = 0.79, $p<0.001$), supporting H9.

Hedonic Motivation: Increased from M=3.27, SD=0.461 to M=4.08, SD=0.382 (mean difference = 0.81, $p<0.001$), supporting H10.

Habit: Increased from M=4.00, SD=0.357 to M=4.55, SD=0.213 (mean difference = 0.55, $p<0.001$), supporting H11.

Facilitating Conditions: Increased from M=3.99, SD=0.377 to M=4.43, SD=0.289 (mean difference = 0.44, $p<0.001$), supporting H12.

Learning Value: Increased from M=3.68, SD=0.449 to M=4.21, SD=0.256 (mean difference = 0.53, $p<0.001$), supporting H13.

Behavioral Intention: Increased from M=3.53, SD=0.335 to M=4.31, SD=0.212 (mean difference = 0.78, $p<0.001$), supporting H14.

The results of the paired-sample t-test have led the researcher to the following conclusions. First, there was a significant difference in the mean scores for all seven variables when comparing the post-IDI stage to the pre-IDI stage. Additionally, the researcher identified a considerable increase in students' behavioral intentions from the pre-IDI phase to the post-IDI phase. This indicates that the intervention or educational development implemented during the IDI stage had a measurable effect on students' intentions to engage in specific behaviors.

5. Conclusions, Recommendations and Limitations

5.1 Conclusions & Discussions

E-learning has transformed education by providing flexible and cost-effective access to resources, allowing students to study from anywhere at any time, thus eliminating geographical and temporal constraints (Allen & Seaman, 2014). Its scalability reduces expenses related to physical materials and infrastructure, resulting in lower tuition costs (Bates, 2015). Moreover, e-learning improves learning outcomes by incorporating multimedia and interactive elements that enhance cognitive processing (Mayer, 2001).

However, despite the many benefits of e-learning, it also presents certain challenges. A significant concern is the digital divide, which means that reliable high-speed internet is not universally available, disproportionately affecting disadvantaged or rural students (Selwyn, 2004). Additionally, the lack of personal interaction in e-learning can lead to feelings of isolation and decreased motivation, as student engagement is often lower compared to traditional educational environments (Moore, 1989). The effectiveness of virtual classrooms also relies on the presence of active learning and social interaction, which are not always consistently present (Kearsley & Schneiderman, 1998).

The study aimed to determine the impact of performance expectancy, effort expectancy, social influence, hedonic motivation, habit, facilitating conditions, and learning value on behavioral intention among students at universities in Shanghai. A comprehensive research design was utilized, employing the Index of Item-Objective Congruence (IOC) for validity and Cronbach's Alpha for reliability, ensuring the credibility of the measurement tools. Data from 100 students were analyzed using multiple linear regression, revealing that performance expectations, effort expectancy, social influence, facilitating conditions, hedonic motivation, habits, and learning value significantly influenced behavioral intention.

The analysis reveals that social influence did not significantly impact university students' behavioral intention to use e-learning platforms. This could be due to students prioritizing personal benefits, such as performance and effort expectancy, over external pressures. Additionally, the normalization of e-learning, especially post-pandemic, may reduce the role of social influence in adoption decisions. Cultural factors might also play a part, with students possibly being more individualistic in their decision-making. These findings suggest that efforts to enhance e-learning adoption should focus on improving the technology's direct benefits rather than relying on peer influence.

5.2 Recommendations

It is recommended that the effectiveness of e-learning platforms be promoted through marketing strategies that highlight success stories and empirical evidence to increase actual usage. Ensuring that these platforms are user-friendly, with intuitive navigation, device compatibility, and clear instructions, is crucial for reducing perceived effort and enhancing utilization. Investment in reliable technical support and robust infrastructure is also advised to encourage regular use of e-learning platforms.

Programs should be designed to be engaging by incorporating gamification, interactive content, and visually appealing interfaces to make learning enjoyable. Additionally, these platforms should be promoted consistently, with the inclusion of daily or weekly tasks that encourage engagement, fostering habitual use. Emphasizing the benefits of e-learning, such as flexibility and access to diverse resources, through testimonials and case studies can help highlight its complementary role alongside traditional education.

Lastly, it is advisable to implement tailored communication strategies that leverage peer influences, such as utilizing student ambassadors or organizing peer-led sessions, to enhance engagement within specific contexts or subgroups.

5.3 Limitations for Future Research

This study, "Factors Impacting Students' Behavioral Intention to Use Electronic Learning in Higher Education in Shanghai, China," offers valuable insights into the factors that influence the adoption of e-learning. However, like any research, it has limitations that indicate areas for future investigation.

Sample Diversity: The study mainly concentrated on students from Shanghai, which may not fully represent the varied student populations across different regions or types of institutions in China. Future research should aim to include a more diverse demographic to enhance the generalizability of the results.

Technological Changes: The rapid pace of technological advancement means that the findings of the current study may become less applicable as new e-learning technologies emerge. Ongoing research is necessary to stay updated with technological innovations and their effects on educational practices.

Psychological Factors: The study primarily addressed external and observable factors that influence behavioral intentions but did not thoroughly examine psychological or intrinsic motivations, such as self-efficacy or personal attitudes toward technology and learning.

References

Ain, N., Shaharum, S. M., & Arshad, M. R. M. (2016). The influence of learning value on the relationship between service quality and student satisfaction: A proposed model. *International Journal of Innovation, Management and Technology, 7*(3), 99-104.

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50*(2), 179-211.

Ali, S., & Arshad, M. (2018). Mobile learning and education: A technology acceptance model approach. *International Journal of Advanced Computer Science and Applications, 9*(5), 18-27.

Allen, I. E., & Seaman, J. (2014). *Grade Change: Tracking Online Education in the United States* (1st ed.). Babson Survey Research Group.

Allen, J., Jimmieson, N. L., & Bordia, P. (2007). Uncertainty during Organizational Change: Managing Perceptions through Communication. *Journal of Change Management, 7*(2), 187-210. https://doi.org/10.1080/14697010701563379

Bates, A. T. (2015). Teaching in a Digital Age: *Guidelines for Designing Teaching and Learning* (1st ed.). Tony Bates Associates Ltd.

Bi, Z., Xu, L. D., & Wang, C. (2014). Internet of Things for Enterprise Systems of Modern Manufacturing. *IEEE Transactions on Industrial Informatics, 10,* 1537-1546. https://doi.org/10.1109/TII.2014.2300338

Billings, D. M., & Halstead, J. A. (2012). *Teaching in Nursing* (4th ed.). Elsevier/Saunders.

Carlson, M., & da Silva, R. (2003). *Method, system, and program for managing multiple resources in a system* (1st ed.). IEEE Xplore.

Chen, Y., & Wu, X. (2017). Exploring the antecedents of students' intention to use e-learning platforms: Perspectives from a developing country. *International Journal of Information and Education Technology, 7*(4), 287-292.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319-340.

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User Acceptance of Computer Technology: A Comparison of Two Theoretical Models. *Management Science, 35*(8), 982-1003. https://doi.org/10.1287/mnsc.35.8.982

Fernandez, A., Lynch, J. G., & Netemeyer, R. G. (2014). Predicting e-learning adoption in Brazil: A mixed-method approach. *Computers & Education, 72*, 10-25.

Gjestvang, C., Abrahamsen, F., Stensrud, T., & Haakstad, L. A. H. (2021). What Makes Individuals Stick to Their Exercise Regime? A One-Year Follow-Up Study Among Novice Exercisers in a Fitness Club Setting. *Front Psychol, 28*(12), 638928. https://doi.org/10.3389/fpsyg.2021.638928

Graham, A. (2006). *Developing Thinking in Statistics* (1st ed.). Sage.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). *Multivariate data analysis: A global perspective* (7th ed.). Pearson Education.

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2013). Partial least squares structural equation modeling: rigorous applications, better results, and higher acceptance. *Long Range Planning, 46*(1/2), 1-12. https://doi.org/10.1016/j.lrp.2013.01.001

Hamzat, O., & Mabawonku, I. (2018). *Adoption of digital library resources and services among undergraduates in selected Nigerian universities* (1st ed.). Library Philosophy and Practice (e-journal).

Hu, X., & Lai, C. (2019). Comparing factors that influence learning management systems use on computers and on mobile. *Information and Learning Sciences, 120*(7/8), 468-488.

Kang, H. Y., & Kim, H. R. (2021). Impact of blended learning on learning outcomes in the public healthcare education course: a review of flipped classroom with team-based learning. *BMC Medical Education, 21*(78), 1-8.

Kearsley, G., & Schneiderman, B. (1998). Engagement theory: A framework for technology-based teaching and learning. *Educational Technology, 38*(5), 20-23.

Li, X., & Li, Y. (2018). The impact of hedonic motivation on the adoption of educational technology among university students in Shanghai. *International Journal of Educational Technology in Higher Education, 15*(1), 29-44.

Luarn, P., Lin, H. H., & Chiu, Y. P. (2015). Influence of online social networks on people's awareness, perception, and acceptance of weather alerts. *Telematics and Informatics, 32*(4), 787-798.

Mayer, R. E. (2001). *Multimedia Learning* (1st ed.). Cambridge University Press.

Means, B., Toyama, Y., Murphy, R., & Bakia, M. (2013). The Effectiveness of Online and Blended Learning: A Meta-Analysis of the Empirical Literature. *Teachers College Record, 115*(3), 1-47. https://doi.org/10.1177/016146811311500307

Ministry of Education of the People's Republic of China. (2010). *MOE press conference presents China's educational achievements in 2023.* http://en.moe.gov.cn/news/press_releases/202403/t20240311_1119782.html

Moore, M. G. (1989). Editorial: Three types of interaction. *American Journal of Distance Education, 3*(2), 1-7. https://doi.org/10.1080/08923648909526659

Oreg, S., Vakola, M., & Armenakis, A. (2011). Change Recipients' Reactions to Organizational Change. *The Journal of Applied Behavioral Science, 47,* 461-524. https://doi.org/10.1177/0021886310396550

Selwyn, N. (2004). Reconsidering political and popular understandings of the digital divide. *New Media & Society, 6*(3), 341-362. https://doi.org/10.1177/1461444804042519

Shanghai Municipal Education Commission. (2015). *Shanghai Municipal Education Commission.* https://en.shanghai.gov.cn/nw46991/20230718/d22e90c5d0c44e6381d7f38817eed849.html

Sharpe, R., Benfield, G., & Roberts, G. (2006). *The undergraduate experience of blended e-learning: a review of UK literature and practice* (1st ed.). Higher Education Academy

Soper, D. S. (2020). *A-Priori Sample Size Calculator for Structural Equation Models [Software].* http://wwwdanielsopercom/statcalc

Sun, Y., & Zhang, H. (2020). Investigating the factors influencing students' intention to use online learning platforms: Evidence from Chinese higher education. *Computers & Education, 146,* 103754.

Tarhini, A., Deh, R. M., 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

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

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425-478. https://doi.org/10.2307/30036540

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly, 36*(1), 157-178.

Verplanken, B., & Wood, W. (2006). Interventions to break and create consumer habits. *Journal of Public Policy & Marketing, 25*(1), 90-103. https://doi.org/10.1509/jppm.25.1.90

Vidakis, N., & Charitakis, K. (2018). E-learning: The new tool for higher education. *International Journal of Advanced Computer Science and Applications, 9*(1), 108-113.

Vroom, V. H. (1964). *Work and motivation* (1st ed.). John Wiley & Sons.

Westland, J. C. (2010). Lower bounds on sample size in structural equation modeling. *Electronic Commerce Research and Applications, 9*(6), 476-487. https://doi.org/10.1016/j.elerap.2010.07.003

Zhang, J. (2016). Can MOOCs be interesting to students? An experimental investigation from regulatory focus perspective. *Computers & Education, 95,* 340-351.

Zhang, L., Fletcher, A. G., Cheung, V., Winston, F., & Stargell, L. A. (2008). Spn1 regulates the recruitment of Spt6 and the Swi/Snf complex during transcriptional activation by RNA polymerase II. *Mol Cell Biol, 28*(4), 1393-1403. https://doi.org/10.1128/mcb.01733-07

Zhang, W., Li, Z., Wang, J., Scarpa, F., & Wang, X. (2022). Mechanics of novel asymmetrical re-entrant metamaterials and metastructures. *Composite Structures, 291,* 115604. https://doi.org/10.1016/j.compstruct.2022.115604