

Factors Impacting Students' Behavior Intension to Use Electronic Learning on Higher Education in Shanghai, China

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Abstract

This study evaluates the effects of Performance Expectancy, Effort Expectancy, Social Influence, Hedonic Motivation, Habit, Facilitating Conditions, and Learning Value on Behavioral Intention among students at Shanghai Universities. Employing the Index of Item-Objective Congruence for validity and Cronbach's Alpha for reliability, 100 valid responses were analyzed using multiple linear regression. A subset of 30 students participated in a 14-week Intervention Design Implementation (IDI), with outcomes analyzed using a paired-sample t-test. The findings indicate that all factors affect behavioral intentions, offering critical insights for enhancing e-learning platform design in higher education. This research provides a solid framework for future studies in this field.

Keywords: Electronic Learning, Performance Expectancy, Effort Expectancy, Social Influence, Habit, Facilitating Conditions, Learning Value, Behavioral Intentions.

Introduction

The rapid progression of information technology and the widespread availability of the Internet have resulted in substantial transformations across various facets of human existence, notably within the worldwide educational arena (Vidakis & Charitakis, 2018). Consequently, educational institutions have been driven to embrace innovative technologies within their pedagogical practices. E-learning has emerged as a favored instructional approach, particularly in the realm of higher education, offering enhanced teaching quality, cost efficiencies in education, and heightened effectiveness in student learning. Universities stand as the primary architects of online education curriculum development, and their contributions in this realm have been pivotal. Shanghai, a vital hub of economic and educational activities in China, has seen its higher education sector evolve into a shining example. While e-learning offers numerous advantages, including convenience, timeliness, and cost-effectiveness, the degree to which students are genuinely inclined to adopt and fully engage in e-learning depends on various influencing factors.

The main impetus for this study arises from the limited research focused on the factors determining students' intentions to embrace e-learning. Consequently, delving into the factors influencing the intentions of Shanghai's higher education students to utilize e-learning holds significant value. It offers insights into students' attitudes and behaviors regarding e-learning, thus serving as a guiding light for universities in their endeavors to implement effective e-learning education strategies.

Objective

1. To investigate the significant impact from performance expectancy toward behavioral intentions.
2. To investigate the significant impact from effort expectations toward behavioral intentions.
3. To investigate the significant impact from social influence toward behavioral intentions.
4. To investigate the significant impact from hedonic motivation toward behavioral intentions.
5. To investigate the significant impact from habits toward behavioral intentions.
6. To investigate the significant impact from facilitating conditions toward behavioral intentions.
7. To investigate the significant impact from learning values toward behavioral intentions.
8. To assess and analyze the current level of Performance Expectancy, Effort Expectancy, Social Influence, Hedonic Motivation, Habit, Facilitating Conditions, Learning Value, and Behavior intention.
9. To design and implement appropriate Intervention Design Implementations on Performance Expectancy, Effort Expectancy, Social Influence, Hedonic Motivation, Habit, Facilitating Conditions, Learning Value to improve Behavior intention.
10. To determine the mean differences of Performance Expectancy, Effort Expectancy, Social Influence, Hedonic Motivation, Habit, Facilitating Conditions, Learning Value, with behavior intention between the pre- and post-strategic plan phases.

Literature Review

Behavioral Intention (BI)

Behavioral intention is a key predictor of actual behavior, driving an individual's willingness and effort to engage in specific actions, often indicating future behaviors (Venkatesh et al., 2003). In research, especially in management studies, behavioral intention is frequently used as a critical variable to understand the decision-making processes of customers. In this study, behavioral intention is treated as a dependent variable, reflecting its importance in predicting actual usage behavior.

Performance Expectancy (PE)

The concept of performance expectancy comes initially from the performance-expectancy theory of motivation, which suggests that motivation is driven by the expectancy of outcomes, the desirability of these outcomes, and the belief in one's ability to perform the actions needed (Vroom, 1964). Research in various educational technology contexts, including digital libraries (Hamzat & Mabawonku, 2018), mobile learning (Ali & Arshad, 2018), and E-learning in data mining (Fernandez et al., 2014), has demonstrated that performance expectations significantly influence usage intentions. Therefore, H1 is represented as:

H1: *Performance Expectancy has significant impact on behavior intention.*

Effort Expectancy

Effort Expectancy, as defined in the technology acceptance model (TAM), refers to the perceived ease of using a system (Davis et al., 1989). This factor significantly influences users' willingness to adopt information technology, particularly in educational settings, where the lower perceived effort leads to quicker system adoption. The impact of effort expectancy on the intention to use learning systems is supported by empirical evidence (Tarhini et al., 2017). This study seeks to empirically validate this theoretical relationship. Therefore, H2 is represented as:

H2: Effort Expectancy has significant impact on behavior intention.

Social Influence

In their study, Luarn et al. (2015) defined social influence as social condition and identified 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. Supporting this, Ain et al. (2016) found that peers and teachers notably influence Malaysian university students' use of mandatory Learning Management Systems (LMS). Therefore, H3 is represented as:

H3: Social Influence has significant impact on behavior intention.

Hedonic Motivation

Hedonic Motivation, rooted in the "hedonic theory of motivation," suggests that human actions are driven by the pursuit of pleasure and avoidance of suffering, as initially proposed by British philosopher Bentham. Research by Chen and Wu (2017) showed that hedonic motivation positively influences students' intentions to use e-learning platforms, indicating that enjoyment in e-learning fosters positive attitudes and usage intentions. Similarly, a study by Li and Li (2018) in Shanghai found that the perception of e-learning as enjoyable significantly impacts university students' willingness to adopt educational technology. Therefore, H4 is represented as:

H4: Hedonic Motivation has significant impact on behavior intention.

Habit

Habit, as defined by Venkatesh et al. (2012), is when an individual's behavior becomes automatic without conscious decision-making, influenced by previous positive experiences with e-learning platforms. This concept suggests that routine use of e-learning can develop into a habit that impacts long-term usage patterns (Verplanken & Wood, 2006). Study by Oreg et al. (2011) supports this, finding that established habits in technology use significantly enhance the intention to continue using e-learning systems. Therefore, H5 is represented as:

H5: Habit has significant impact on behavior intention

Facilitating Conditions

Venkatesh et al. (2003) describe convenience in technology adoption as the support and technical assistance available to users, such as help desks and support menus. Zhang (2016) highlights how matching teaching approaches to students' regulatory focuses and "happy" areas can significantly motivate them to use and learn from MOOCs. Additionally, Hu and Lai (2019) found that the availability of technical support and necessary skills for using learning management systems (LMS) on various devices influences students' expectations and willingness to use these systems. Therefore, H6 is represented as:

H6: Facilitating Conditions has significant impact on behavior intention.

Learning Value

Ain et al. (2016) define Learning Value (LV) as the perceived benefits and overall value students attribute to their e-learning experiences, considering the time and effort invested rather than monetary cost. In technology adoption, Venkatesh and Davis (2000) introduced the Technology Acceptance Model (TAM), highlighting perceived usefulness, closely related to learning value. Sun and Zhang (2020) found that students in China are more likely to engage with online platforms when they perceive the learning as valuable for knowledge acquisition and academic improvement. Therefore, H7 is represented as:

H7: Learning Value has significant impact on behavior intention.

Conceptual Framework

Researcher applied three model theories from Technology acceptance model (Davis, 1989), Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003) and Theory of Planned Behavior (Ajzen, 1991). All three theoretical frameworks mentioned above supported and developed conceptual framework in Figure 1.

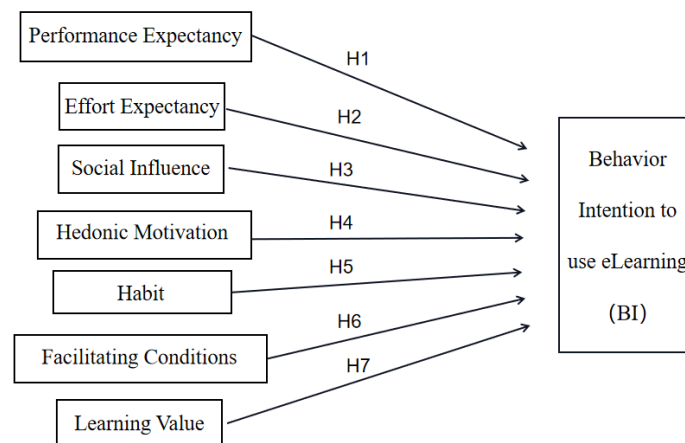


Figure 1: Conceptual Framework

Research Methodology

The research process consisted of four stages, starting with surveying the entire research population (n=105) to collect data for the conceptual framework. Hypotheses were then tested using multiple linear regression, retaining those supported at a p-value threshold of < 0.05 and discarding others. The second stage involved pre-IDI surveys among the same 105 students. The third stage saw the implementation of the Intervention Design Implementation (IDI) with 30 participants which from the department of Education. In the final stage, these 30 participants completed post-IDI surveys, and the data collected was analyzed using paired-sample t-tests to compare pre- and post-IDI results, enabling a detailed evaluation of the research objectives and hypotheses.

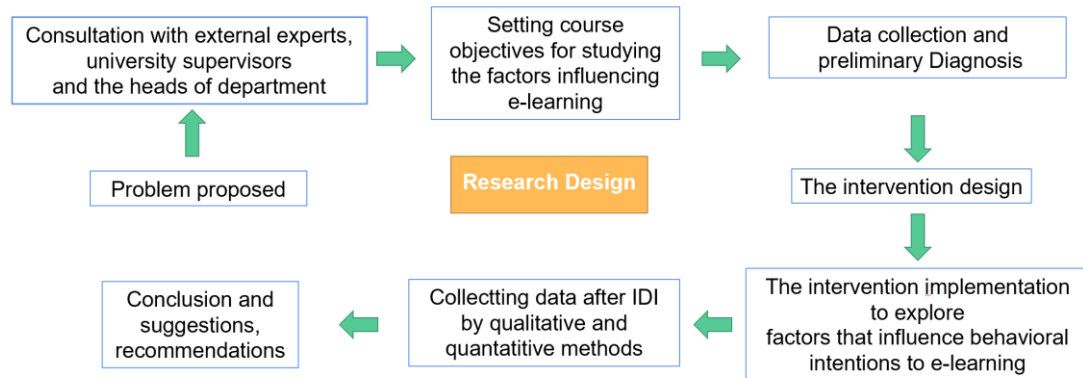


Figure 2: Research Design

Researcher invited five independent experts or scholars or doctors to implement IOC (Index of item-objective congruence). In this research, all questionnaire items were greater than 0.67, so researcher retained all questionnaire items.

Researcher implemented pilot survey to 5 teachers and 10 students asking them to fill the survey questionnaire, and to give feedback. Therefore, below table demonstrated the approved results for high reliability of each construct.

Table 1: Pilot Test Result

Variable	No. of Items	Cronbach's Alpha (α)	Strength of Association
Performance Expectancy	4	0.762	Acceptable
Effort Expectancy	4	0.815	Good
Social Influence	4	0.742	Acceptable
Hedonic Motivation	4	0.728	Acceptable
Habit	4	0.811	Good
Facilitating Conditions	4	0.813	Good
Learning Value	4	0.796	Acceptable

Research Finding

Results

Demographic Profile

Researcher demonstrated demographic profile of entire research population (n=100) as shown in Table 2.

Table 2: Demographic Profile

Variable		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%
Grade	Freshmen	12	12%
	Sophomores	25	25%
	Juniors	31	31%
	Seniors	31	31%

Results of multiple linear regression

The R-squared (R^2) in a multiple linear regression model with seven independent variables can account for 48.6% of the variability in behavior intention.

Table 3: The multiple linear results of the seven independent variables on behavior intention

Variables	Standard Coefficients Beta	t	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 revealed that all seven independent variables significantly influenced the dependent variable, as indicated by p-values less than 0.05. The R-squared value of 0.468 means that these variables explain approximately 46.8% of the variance in the dependent variable. All normalized regression coefficients were positive, suggesting a positive correlation between the independent and dependent variables. The standardized regression coefficients showed that performance expectancy, effort expectancy, social influence, hedonic motivation, habits, facilitating conditions, and learning value had a significant impact on behavioral intention reflected by their respective coefficients (0.471, 0.375, 0.205, 0.260, 0.288, 0.257).

The following finalized research hypothesis are related to the changes between pre-and post-IDI on all the subvariables.

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

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

H10: There is a significant difference in Social Influence between Pre--IDI and Post-IDI stages.

H11: There is a significant difference in Hedonic Motivation between Pre--IDI and Post-IDI stages.

H12: There is a significant difference in Habit between Pre-IDI and Post-IDI stages.

H13: There is a significant difference in Facilitating Conditions between Pre-IDI and Post-IDI stages.

H14: There is a significant difference in Learning Value between Pre-IDI and Post-IDI stages.

H15: There is a significant difference in Behavior intention between Pre-IDI and Post-IDI stages.

IDI Intervention Stage

The comprehensive development of the IDI phase spans a duration of 14 weeks.

Table 4: Implementation time and 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

Results Comparison between Pre-IDI and Post-IDI

Researcher implemented paired-sample t-test analysis on all seven variables to identified whether there were any differences in behavioral intentions towards using e-learning between the pre-IDI and post-IDI phases. Totally, the below tables to illustrate paired-sample t-test analysis on seven variables as follow:

Table 5: Paired-Sample T-Test Result

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	
Social Influence				
Pre-IDI	3.49	0.346	0.0632	p<0.01
Post-IDI	4.55	0.246	0.0449	
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 presents the paired-sample t-test results for pre-IDI and post-IDI comparisons. Significant increases were observed 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.

Social Influence: Increased from M=3.49, SD=0.346 to M=4.55, SD=0.246 (mean difference = 1.06, P<0.001), supporting H10.

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 H11.

Habit: Increased from M=4.00, SD=0.357 to M=4.55, SD=0.213 (mean difference = 0.55, P<0.001), supporting H12.

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 H13.

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 H14.

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 H15.

According to paired-sample t-test results demonstrated above; researcher came up with following conclusions. First, all seven variables had significant mean difference between post-IDI stage and pre-IDI stage. Second, researcher found out that there was significant increase on Students' Behavior intention between the pre-IDI and post-IDI phases.

Discussion

E-learning has transformed education by providing flexible and cost-effective access to resources, allowing students to study anywhere and anytime, thus overcoming geographical and temporal barriers (Allen and Seaman, 2014). Its scalability reduces expenses related to physical materials and infrastructure, lowering tuition fees (Bates, 2015). E-learning also improves learning outcomes through the integration of multimedia and interactive elements, enhancing cognitive processing (Mayer, 2001).

However, e-learning faces challenges such as the digital divide, where reliable high-speed internet is not universally available, disproportionately affecting disadvantaged or rural students (Selwyn, 2004). The lack of personal interaction in e-learning can lead to isolation and reduce student motivation, as personal engagement is less compared to traditional settings (Moore, 1989). Furthermore, the effectiveness of virtual classrooms depends heavily on active learning and social interaction, which are not always present (Kearsley and Schneiderman, 1998).

Conclusion

The study assessed how Performance Expectancy, Effort Expectancy, Social Influence, Hedonic Motivation, Habit, Facilitating Conditions, and Learning Value influence behavioral intention among students at Shanghai Universities. Employing a robust research design, the study used the Index of Item-Objective Congruence (IOC) for validity and Cronbach's Alpha for reliability, ensuring the measurement instruments' credibility. Data from 100 students underwent multiple linear regression analysis, showing that performance expectations, effort expectancy, social influence, facilitating conditions, hedonic motivation, habits, and learning value significantly impact behavioral intention.

A 14-week Intervention Design Implementation (IDI) was conducted with a group of 30 students, and a paired-sample t-test comparing pre-ID and post-ID data indicated a positive impact on all factors, enhancing behavioral intentions toward e-learning. These findings highlight important insights for higher education institutions in promoting e-learning platforms and contribute to understanding and addressing the challenges in e-learning, ultimately aiding in the improvement of e-learning methods.

Enhance performance expectations by prioritizing the communication of e-learning platforms' effectiveness through marketing that showcases success stories and empirical evidence to boost actual usage. Ensure these platforms are user-friendly with intuitive navigation, compatibility across devices, and clear instructions to reduce perceived effort

and enhance usage. Invest in reliable technical support and robust infrastructure to encourage regular use of e-learning platforms. Design programs to be engaging through gamification, interactive content, and visually appealing interfaces, making learning enjoyable. Promote regular interaction with these platforms by incorporating daily or weekly tasks that require platform engagement, thus fostering habitual use. Emphasize the benefits of e-learning, such as flexibility and access to diverse resources, through testimonials and case studies, highlighting its complementary role to traditional education. Finally, utilize tailored communication strategies involving peer influences, like student ambassadors or peer-led sessions, to enhance engagement in specific contexts or subgroups.

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