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Understanding Factors Affecting Behavioral Intention to Use Blended Learning of Business Major Undergraduates in a Public University in Chengdu, China

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Abstract

Purpose: Given the advancements in information technology and the implications of COVID-19 on education, the blended learning can enhance accessibility to university education. The study examines the factors influencing business major undergraduates' behavioral intention towards blended learning. **Research design, data, and methodology:** Data were gathered quantitatively from a sample of 500 undergraduate students using an organized electronic questionnaire. The researchers employed judgmental sampling and quota sampling. The data analysis method used was structural equation modeling, and confirmatory factor analysis (CFA) was used to verify the validity of the data gathered. **Results:** The data analysis results fully validated all of the hypotheses, with attitude showing the most direct influence on undergraduate business majors' behavioral intention in blended learning. Perceived usefulness and perceived ease of use significantly affect attitude. Social influence, self-efficacy and facilitating conditions have a significant effect on behavioral intention. **Conclusions:** To facilitate the progress of blended learning, university administrators, educators, and students need to consider various elements that influence students' willingness to use blended learning. Furthermore, according to the study's findings, efforts should be made to improve undergraduates' perceptions of the utility and usability of blended learning to improve their favorable attitude towards it, thereby further promoting their intention to adopt it.

Keywords: Blended Learning, Facilitating Conditions, Attitude, Social Influence, Behavioral Intention

JEL Classification Code: E44, F31, F37, G15

1. Introduction

In 2010, the Chinese government proclaimed the Outline of the National Medium- and Long-Term Plan for Educational Reform and Development (2010-2020), emphasizing the transformative influence of information technology on the evolution of education and calling for further advancement of educational informatization. As information technology evolves, artificial intelligence undergoes continuous transformation, while network big data technology demonstrates an unwavering development trend (Yu, 2023). Consequently, the application of information technology in education is now undergoing a consistent and gradual rise (Chen, 2022).

There has been a noticeable surge in the number of online courses offered in China during the COVID-19 pandemic, with 1.08 million educators providing 17.19 million courses in undergraduate universities nationwide and an impressive enrollment of 3.5 billion undergraduates participating in online learning, accounting for a remarkable 91% of the student population across the country. Based on statistics from the Ministry of Education, PRC, as of 2022, China's online MOOCs have surpassed 50,000 in quantity, attracting approximately 800 million individuals who have chosen various courses and empowering over 300 million students to earn MOOC credits (Yu, 2023).

Business majors exhibit strong practicality and application skills, with many hybrid courses incorporating

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information technologies such as VR, AR, virtual simulation, big data, and artificial intelligence (Jin & Zhang, 2023). Previous studies have demonstrated that positive behavioral intentions significantly enhance learning outcomes in the context of blended learning (Wang & Fu, 2018). However, the rapid expansion of blended courses has led to issues such as limited interaction during teaching processes, inadequate authenticity in evaluation methods, reduced opportunities for practical instruction, and declining learning efficiency among students (Yang et al., 2021). Hence, it was imperative to thoroughly analyze the factors influencing business major students' adoption of blended learning.

This was the format of the current study: the conceptual model and research hypotheses were offered in the third section, and a thorough survey of pertinent literature was supplied in the second. The research technique was covered in the fourth section, and data analysis was covered in the fifth. In the final phase, this study was concluded in the last section.

2. Literature Review

2.1 Perceived Usefulness

Users' perceived usefulness of the software platform was a reliable indicator of their happiness through it (Tarhini, 2013). Through their cognition, the learner feels that the software is effective for self-learning, leading to the recognition of the tool. It was how much a student believed that a particular educational model would advance his or her capacity for learning (Wang et al., 2003). In education, PU showed advantages when using internet-based materials at a particular time and location to support and change study (Chen & Tseng, 2012). To put it another way, it evaluated the extent to which college students perceive the utilization of a learning system to increase their academic performance (Pramana, 2018). College students judged whether the tool was effective and the degree to which the tool improved learning effectiveness through their knowledge, cognition, and other factors.

Perceived usefulness is a critical component of TAM and can be used to measure the quality of a website. Several earlier studies identified the depth of perceived usefulness as a crucial element in determining customers' expectations to embrace the target system (Venkatesh & Davis, 2000). According to Cigdem and Ozturk (2016), perceived usefulness typically added to the association of clients' achievement. That meant PU could boost the learner's performance if they had a strong recognition of the tool and considered it effective; then, using the device can boost their performance in their studies. It has been regarded as a major indicator of teacher satisfaction in education (Ramdhony et al., 2021). In other words, users' PU of digital technology services can influence how satisfied they are with the services (Wang et al., 2019). Consequently, a hypothesis is indicated:

H1: Perceived usefulness has a significant effect on attitude.

2.2 Perceived Ease of Use

Perceived ease of use, according to Ramdhony et al. (2021), revealed that implementing novel technology may be straightforward and easy to understand, operate, or use. Moreover, the degree to which it was thought that applying an internet-based educational system would be easy was defined as perceived ease of use within the framework of online education (Venkatesh & Davis, 2000). Wang et al. (2003) explained that it described how much people thought that implementing a certain system may increase its productivity as well as the perceived value of an app like this network. This process is centered on the capacity to adapt, operate, and use something effectively. In 2014, Tagoe and Abakah presented that the degree to which participants were persuaded that using electronic instructional resources would be convenient was perceived as ease of use in technical terms.

Numerous research studies have extensively investigated the notion of perceived ease of use as a critical component in shaping users' behavioral inclination towards a particular information system. Two indirect impacts of perceived ease of use were postulated by Davis et al. (1989) in their TAM, and they had two indirect effects on behavioral intention: one through attitude and the other through perceived usefulness. For Fokides (2017), perceived ease of use dramatically influenced attitudes regarding implementing digital learning. According to Agarwal and Karahanna (2000), perceived ease of use had a favorable and significant impact on people's propensity to utilize new technology. Although it had a less significant effect, Ali et al. (2018) found that the perceived ease of use of the online learning system impacted the motivation to utilize an e-learning platform. Consequently, a hypothesis is indicated:

H2: Perceived ease of use has a significant effect on attitude.

2.3 Attitude

According to the social cognition hypothesis, attitudes were behavioral dispositions towards societal elements, things, views, or signals acquired over time. (Venkatesh et al., 2003). Besides, Ramdhony et al. (2021) mentioned that users' attitudes toward online teaching resources might reflect their perceptions, views, or feelings, whether positive or negative. From the psychology perspective, Ajzen (1991) redefined an individual's attitude as their enduring intention towards something. When individuals possess desires, they may exhibit favorable and unfavorable behaviors to achieve their objectives. Attitude refers to a person's persistent psychological inclination toward a certain item, such as a person, idea, emotion, or event (Tagoe & Abakah, 2014).

Attitude is a complex concept relating to psychology. Thus, it was necessary to study how a person's attitude was influenced by their surrounding environment and other factors and their mutual influence. A positive attitude may influence behavior and inspire an enthusiasm for learning, which can help people use learning platforms more successfully (Long & Khoi, 2020). Besides, Abdallah et al. (2019) argued that one of the biggest challenges to ensuring students' sustainability and favorable attitude toward online education was the increasing proliferation of online learning in the realm of colleges and universities. Attitude towards using an unfamiliar platform affects users' intention to use online applications (Tan, 2013). Users' attitudes and abilities to use the platform were influenced by its functionality (Salloum et al., 2018). Consequently, a hypothesis is indicated:
H3: Attitude has a significant effect on behavioral intention.

2.4 Social Influence

Social influence was a key determinant of whether people would adopt technology breakthroughs like online information or e-learning platforms (Tarhini et al., 2017). Numerous research has verified the notion of SI as an essential element in predicting users' intentions to embrace technologies like online learning. According to Al-Mamary et al. (2015), this was also the extent to which students felt the need to adhere to social pressure because they perceived it or anticipated engaging in a particular activity. According to Foon and Fah (2011), the social status of an individual or group affects the acceptability of certain terminology created for them by technology. It was noted as an important variable in implementing the e-learning platform. Social influence refers to how other human beings manipulate users' behavior when engaging with technology (Dakduk et al., 2018).

Previous research on e-learning, mobile learning, and ubiquitous learning has provided valuable insights into the emergence of social norms and their implications for technology usage. Venkatesh et al. (2003) also stated that compulsory usage and the significance of social influence have been demonstrated, especially in the early stage of the adoption of social influence. This word means the environment has an impact on how people make use of technological devices. Social influence was one of the determinants affecting students' adoption of portable education technologies (Pramana, 2018). Moreover, Mittal et al. (2021) presented that social influence could boost the members' behavior as they adopted and reacted to a certain method. Other researchers illustrated this variable; for Raman et al. (2022), it represented other people's perceptions of their decision regarding utilizing an information system. Consequently, a hypothesis is indicated:
H4: Social influence has a significant effect on behavioral intention.

2.5 Self-Efficacy

Self-efficacy measures a person's competence to operate relevant technology, such as computers, mobiles, or pads, to carry out certain activities or tasks (Venkatesh et al., 2003). Tarhini (2013) described it as how an individual thought of their ability to utilize laptops for carrying out tasks. Later, technological advancement, especially information and communications technology (ICT), became a subjective assessment of whether a person can successfully use specific information devices for a certain behavior. Self-efficacy refers to a person's assessment of their competence to use computers in various situations (John, 2015). For Fokides (2017), self-efficacy was described as a person's evaluation of their ability to utilize new software, platforms, or electronic devices to complete tasks instead of only reflecting simple abilities.

The core idea of self-efficacy was a person's evaluation of their ability to use tools like computers and the internet. Self-efficacy is a sort of self-evaluation that aids in understanding how people act and perform in a particular activity (Valtonen et al., 2015). Computer self-efficacy has been demonstrated to be favorably related to digital learning effects as evaluated by average test scores (Tan, 2013). Self-efficacy in connection with virtual learning refers to how students assess their competencies to implement hybrid learning projects (Tagoe & Abakah, 2014). According to Wang et al. (2019), computer self-efficacy substantially predicted students' desire for further using the internet learning programs. Consequently, a hypothesis is indicated:
H5: Self-efficacy has a significant effect on behavioral intention.

2.6 Facilitating Conditions

The extent to which a person thought the existing organizational and technical infrastructure could support the usage of the system" was how Venkatesh et al. (2003) defined facilitating conditions, and they incorporated this definition into the UTAUT model, which other authors have widely adopted. Tan (2013), the term describes how much a person's environment helped this person engage in a certain behavior. It implied the user's thoughts that organizational infrastructure and support were accessible to help apply this specific technique (Venkatesh et al., 2012). In terms of telecommunications and information technology, it could be seen as a condition for the relevant resources provided by the user. According to Ali et al. (2018), it symbolizes how well the current institutional and technological infrastructure supports technology implementation.

Facilitating conditions stressed the need for a robust and reliable design for the Blackboard software's acceptance and reliance on the internet-based education environment (Venkatesh et al., 2003). Lwoga and Komba (2015) used UTAUT to predict the factors influencing the willingness of two groups of Tanzanian students and teachers to continue using web-based learning management systems (LMS). They indicated that self-efficacy, performance expectations, effort expectations, and facilitating conditions significantly impact the actual use of e-learning systems. Additionally, according to Mittal et al. (2021), facilitating conditions were provided externally to give students access to online instruction services. It was an environmental component that influenced the users' views of whether a tough or simple task was to be fulfilled (Salloum et al., 2018). Consequently, a hypothesis is indicated:

H6: Facilitating conditions has a significant effect on behavioral intention.

2.7 Behavioral Intention

A person's decision to be involved in a distinctive task in the future was regarded as their behavioral intention (Cigdem & Ozturk, 2016). Behavior intention was characterized as a behavioral propensity to continue utilizing advanced technology; as a result, it assessed technology adoption (Alharbi & Drew, 2014). Fokides (2017) noted that somebody's judgment of their competence to carry out a certain act successfully influenced their choice of purpose. This was referred to as behavioral intention, emphasizing how crucial it was to comprehend something before committing to it. A factor influencing technology usage was known as psychological intent to adopt, which was started by the learners' selection of whether to continue utilizing this technology (Chen & Tseng, 2012).

Many scholars showed that exogenous variables, such as performance expectation, effort expectation, social impact, quality of work life, hedonic motivation, network experience, and convenience, notably influenced behavioral intention and use behavior of adopting e-learning systems (Zhang et al., 2012). Intentional behavior is a key sign of how well a system or piece of technology is used (Salloum et al., 2018). For Davis et al. (1989), the notion of intent to use arose from the technology adoption paradigm, which advocated users' perception and simplicity of software to support intent to use the new tech once more. According to Ajzen (1991), success in online learning settings is partly attributed to learners' behavioral intent to engage in virtual learning.

3. Research Methods and Materials

3.1 Research Framework

By amalgamating methodologies from previous research on blended learning, this study constructs a conceptual framework that unifies three validated models rooted in C-TAM-TPB and UTAUT theories. According to Jnr et al. (2020), students' behavioral intention to accept blended learning is influenced by attitude and self-efficacy. Bagdi et al. (2023) established that perceived usefulness (PU) and perceived ease of use (PEU) have an impact on attitude, subsequently affecting the behavioral intention to adopt blended learning. Additionally, applying UTAUT2, as demonstrated by Rudhumbu (2022), revealed that social influence and facilitating conditions significantly and positively contribute to the behavioral intention of higher education students to adopt blended learning. Figure 1 illustrates the conceptual framework of this research.

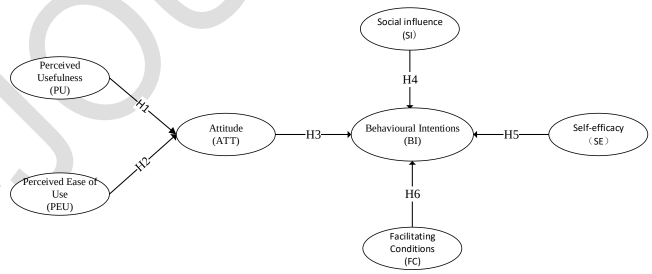

Figure 1: Conceptual Framework

H1: Perceived usefulness has a significant effect on attitude.
H2: Perceived ease of use has a significant effect on attitude.
H3: Attitude has a significant effect on behavioral intention.
H4: Social influence has a significant effect on behavioral intention.
H5: Self-efficacy has a significant effect on behavioral intention.
H6: Facilitating conditions has a significant effect on behavioral intention.

3.2 Research Methodology

This study aims to ascertain the behavioral intention of undergraduate business majors at Xihua University in Sichuan, China, toward blended learning. The most efficient research methodology for gathering attitude data from students and determining their intention to use was the quantitative survey approach used in this study.

In this research, quantitative methodologies were utilized, specifically incorporating the project-objective consistency

(IOC) test and Cronbach's Alpha test. A panel of three experts evaluated the Index of Item-Objective Congruence (IOC) to verify that each item accurately captures its intended construct, thus contributing to the enhancement of the assessment's validity. The pilot test, conducted with 50 participants, demonstrated a Cronbach's Alpha score surpassing 0.7, affirming the dependable measurement of the specified construct and bolstering the overall reliability of the test results, consistent with the guidelines outlined by Nunnally and Bernstein (1994).

Participants in educational settings were given a survey instrument created with validated items from earlier investigations. Participants provided their demographic information and responded to 27 statements across seven constructs. Five factors were related to perceived utility, three to perceived ease of use, five to attitudes, four to social impact, three to enabling conditions, three to self-efficacy, and four to behavioral intention. Bagdi et al. (2023) was the source of the claims regarding perceived usefulness, perceived ease of use, and attitude. The statements on behavioral intention, facilitating conditions, and social influence were adapted from Rudhumbu's study published in 2022. Self-efficacy was adapted from Ali Tarhini et al. (2017). This study displayed the five-point Likert scale used to score each item, with one representing strongly disagree and five representing strongly agree.

3.3 Population and Sample Size

The target population for the survey included all undergraduate students majoring in business at Xihua University, encompassing those studying Business Administration, Accounting, Financial Management, Human Resource Management, and Supply Chain Management.

Wolf et al. (2013) discovered that the necessary sample sizes varied from 30 (for a Simple Confirmatory Factor Analysis with four metrics and loadings approximately at 0.80) to 450 instances (for mediation models). Therefore, considering the possibility of invalid data in the survey, 1104 pupils in the population and 500 students made up the final sample size following screening and quota selection.

3.4 Sampling Technique

The researchers employed a multi-phase sampling approach, commencing with judgment sampling, to identify 1,104 undergraduate business majors from target universities who had undergone blended learning experiences. In the subsequent step, quota sampling was utilized to select a final sample of 500 respondents from the initial pool of 1,104 undergraduate students. After the completion of data collection, a total of 472 valid questionnaires and 28 invalid questionnaires were obtained.

Table 1: Sample Units and Sample Size

Xihua University	Population Size	Proportional Sample Size
Business Administration	247	112
Accounting	253	115
Financial Management	181	82
Human Resource Management	198	89
Supply Chain Management	225	102
Total	**1104**	**500**

Source: Constructed by author

4. Results and Discussion

4.1 Demographic Information

The demographic characteristics of 472 valid samples are displayed in Table 2. Regarding gender distribution, males account for 44.92%, while females comprise 55.08%. Regarding the major direction, Business Administration represents 22.67%, Accounting accounts for 22.03%, Financial Management comprises 16.53%, Human Resource Management constitutes 18.01%, and Supply Chain Management makes up 20.76%. When examining grade levels, first-year students represent approximately 19.28% of the total, sophomores account for around 27.12%, juniors comprise about 28.60%, and seniors constitute approximately 25%.

Table 2: Demographic Profile

Demographic and General Data (N=472)		Frequency	Percentage
Gender	Male	212	44.92%
	Female	260	55.08%
Major Direction	Business Administration	107	22.67%
	Accounting	104	22.03%
	Financial Management	78	16.53%
	Human Resource Management	85	18.01%
	Supply Chain Management	98	20.76%
Academic Year	1st Year	91	19.28%
	2nd Year	128	27.12%
	3rd Year	135	28.60%
	4th Year	114	24.31%

4.2 Confirmatory Factor Analysis (CFA)

The CFA has gained widespread recognition as a crucial analytical tool across various social and behavioral sciences domains. This capability enables scientists to examine the causal connections between latent and observed variables within pre-specified models derived from theoretical frameworks. The primary advantage of CFA lies in its ability to assist scholars in addressing the disparity between theoretical concepts and practical findings (Mueller & Thomas, 2001).

According to Table 3's results, every average extracted variance (AVE) value was higher than the acceptable level of 0.50, every composite reliability (CR) value was higher than the acceptable level of 0.70, and every factor loading value was higher than the minimal requirement of 0.50.

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
Perceived Ease of Use (PEU)	Bagdi et al. (2023)	0.878	5	0.703-0.732	0.765	0.521
Self-Efficacy (SE)	Tarhini et al. (2017)	0.850	3	0.787-0.851	0.855	0.663
Facilitating Conditions (FC)	Norman Rudhumbu (2022)	0.817	3	0.711-0.822	0.814	0.594
Social Influence (SI)	Norman Rudhumbu (2022)	0.865	4	0.739-0.858	0.866	0.619
Perceived Usefulness (PU)	Bagdi et al. (2023)	0.842	3	0.774-0.869	0.923	0.705
Attitude (ATT)	Bagdi et al. (2023)	0.834	5	0.794-0.874	0.880	0.596
Behavioral Intention (BI)	Norman Rudhumbu (2022)	0.870	4	0.740-0.855	0.765	0.521

All pertinent incremental fit measures (e.g., CFI) benchmarks, and absolute fit indicators (CMIN/DF, GFI, AGFI, and RMSEA) meet the specified criteria, as outlined in Table 4. Consequently, each goodness-of-fit metric utilized in the Confirmatory Factor Analysis (CFA) analysis was considered satisfactory.

Table 4: Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	<3 Hair et al. (2010)	2.651
GFI	>0.90 Bagozzi and Yi (1988)	0.904
AGFI	>0.80 Sica and Ghisi (2007)	0.850
RMSEA	<0.05 Pedroso et al. (2016)	0.047
CFI	>0.90 Hair et al. (2010)	0.947
NFI	>0.90 Hair et al. (2010)	0.921
TLI	>0.90 Bentler and Bonett (1980)	0.939
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, CFI = Comparative fit index, NFI = Normed fit index and TLI = Tucker-Lewis index.

The findings regarding discriminant validity are shown in Table 3. No correlation of more than 0.80 was found between any two latent variables, and the diagonal elements reflect the square root of AVE. Therefore, discriminant validity was proven using these quantitative measurements.

Table 5: Discriminant Validity

	PU	PEU	FC	SI	SE	ATT	BI
PU	**0.721**						
PEU	0.646	**0.814**					
FC	0.586	0.727	**0.770**				
SI	0.647	0.660	0.683	**0.786**			
SE	0.520	0.679	0.677	0.681	**0.839**		
ATT	0.661	0.679	0.728	0.719	0.691	**0.772**	
BI	0.612	0.644	0.724	0.777	0.732	0.723	**0.816**

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

4.3 Structural Equation Model (SEM)

Following an assessment of confirmatory factor analysis (CFA), the structural equation model (SEM) was verified in this study. An individual set of linear coefficients was evaluated using the SEM technique to see how well it fit the proposed causal explanation. Additionally, SEM examined the causation connection between the attributes of a given matrix while considering potential bias in coefficient assessment. According to Table 6, after adjusting using the AMOS software program, all metrics had acceptable thresholds: CMIN/DF, GFI, AGFI, CFI, NFI, TLI, and RMSEA. Consequently, the SEM demonstrated a satisfactory level of goodness-of-fit.

Table 6: Goodness of Fit for Structural Model

Index	Acceptable	Statistical Values
CMIN/DF	<3 Hair et al. (2010)	2.950
GFI	>0.90 Bagozzi and Yi (1988)	0.911
AGFI	>0.80 Sica and Ghisi (2007)	0.818
RMSEA	<0.05 Pedroso et al. (2016)	0.042
CFI	>0.90 Hair et al. (2010)	0.916
NFI	>0.90 Hair et al. (2010)	0.902
TLI	>0.90 Bentler and Bonett (1980)	0.924
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, CFI = Comparative fit index, NFI = Normed fit index and TLI = Tucker-Lewis index.

4.4 Research Hypothesis Testing Result

Based on the calculated results in Table 8, the results of the path analysis indicated that all direct paths were statistically significant, thus supporting hypotheses H1–H6. The most direct relationship between attitude and behavioral intention resulted in a standardized path coefficient (β) of 0.600 (t-value of 12.368, p<0.001). Additionally, the second most important factor that significantly influenced behavioral intention was self-efficacy, with β at 0.492 (t-value at 10.012, p<0.001); after that, attitude had β at 0.279 (t-value at 6.738, p<0.001) and facilitating situations had β at 0.306 (t-value at 7.297, p<0.001). Furthermore, attitude was significantly influenced by perceived usefulness and perceived ease of use. With β at 0.567 (t-value at 10.296, p<0.001), perceived ease of use had the largest impact on attitude, followed by perceived usefulness at 0.410 (t-value at 11.600, p<0.001).

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-value	Result
H1: PU→ATT	0.410	11.600***	Supported
H2: PEU→ATT	0.567	10.296***	Supported
H3: ATT→BI	0.600	12.368***	Supported
H4: SI→BI	0.279	6.738***	Supported
H5: SE→BI	0.492	10.012***	Supported
H6: FC→BI	0.306	7.297***	Supported

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

Hypothesis 1 posits that the perceived usefulness during blended learning impacts students' usage attitude, subsequently influencing their adoption behavior intention towards blended learning. A standardized path coefficient of 0.410 is found. In educational technology, a substantial body of research demonstrates that attitudes toward adopting new technologies are influenced by perceived usefulness. (Al-Emran et al., 2021; Buabeng-Andoh, 2018; Gupta, 2020)

The statistical results of hypothesis 2 indicated that with a standardized coefficient value of 0.567, perceived ease of use had a substantial effect on usage attitude; perceived ease of use of modern digital technologies contributed to creating a favorable mindset for technology adoption, particularly in the field of education (Abdelwahed & Soomro, 2023; Riyath & Rijah, 2022; Singh & Tewari, 2021).

The analysis results of hypothesis 3 indicated that attitude significantly influenced behavioral intention in blended learning, as evidenced by the 0.600 value of the standardized path coefficient. Jnr et al. (2020) applied TPB to study determinants of the execution of blended learning in college and university institutions. They found that students' attitude positively predicted their intention to accept blended education.

The analysis results of hypothesis 4 indicated that social influence significantly influenced behavioral intention in blended learning, as evidenced by the result of 0.279 for the standardized path coefficient. The effect of social factors played a crucial role when the use of devices became inevitable (Venkatesh et al., 2003). This was particularly evident during and after the COVID-19 pandemic (Raza et al., 2022).

The analysis results of hypothesis 5 indicated that Self-efficacy has a major impact on behavioral intention in blended learning, as evidenced by the value of 0.492 for the standardized route coefficient. Yang et al. (2021) identified that computer self-efficacy was a key variable driving the effective usage of online learning in a study done at a scientific institution in Taiwan.

The analysis results of hypothesis 6 revealed a substantial relationship between enabling factors and behavioral intention in blended learning, as evidenced by the 0.306 value of the standardized path coefficient. Lwoga and Komba (2015), on usage intentions of an accessible learning management system via the Internet in Tanzania, confirmed that factors of facilitating conditions had an immediate and considerable effect on students' actual usage of web-based learning management systems (LMS).

5. Conclusion and Recommendation

5.1 Conclusion and Discussion

This study aimed to determine the significant factors influencing the behavioral intention of undergraduate students majoring in business toward adopting blended learning. The conceptual framework proposed six hypotheses to examine the interplay between perceived ease of use, perceived usefulness, facilitating conditions, social influence, attitude, self-efficacy, and behavioral intention. To investigate these relationships, a survey was distributed to 500 undergraduate students who had previously engaged in blended learning. Based on previously published research, the authors' measuring model was examined using confirmatory factor analysis (CFA) to see if the data they had gathered agreed with it. Additionally, in order to test the suggested hypotheses gradually and assess the relationships between the observable and latent factors that affected the adoption of blended learning, structural equation modeling, or SEM, was employed. Findings from this study indicate that attitude exerted the most substantial direct influence on behavioral intention. Perceived ease of use demonstrated a strong effect on attitudes. Furthermore, the factors that greatly affected behavioral intention were self-efficacy, facility conditions, and social influence.

5.2 Recommendation

The researchers provide suggestions based on the results of this investigation. Firstly, the main factor impacting students' behavioral intention to adopt blended learning is their attitude. Students' attitude is influenced by two factors: perceived ease of use and perceived usefulness. Therefore, from these two angles, it is essential to strengthen students' favorable attitudes toward blended learning. From the perceived ease of use, course developers should personalize learning push services for learners by offering diverse forms, of course, content display and guidance modules catering to individual learner characteristics.

Additionally, the blended course management platform should incorporate comprehensive search and navigation functions, simplify system operations, and enhance student user experience. Regarding perceived usefulness, teachers should present course and unit goals to students while emphasizing their value. This approach ensures that students understand "what" they need to learn and "why" they are learning it, thus stimulating their interest and motivation towards the course and its content.

Secondly, an important factor in determining students' behavioral intention to embrace blended learning is their level of self-efficacy. Consequently, teachers should provide learners with a well-defined learning path, study guide, and guidance on effective blended learning methods. Monitoring progress throughout blended learning activities enables timely feedback provision as well. Students can improve their self-efficacy by training themselves to accurately assess knowledge gaps, develop problem-solving strategies, and engage in reflective practices.

Thirdly, educational authorities at universities must strengthen the software and hardware facilities required for implementing blended teaching approaches to ensure the smooth execution of blended courses.

Ultimately, the education authorities in schools should expand the availability of blended courses and offer students a wider range of options. Within blended learning, teachers should actively foster cooperative learning and interactive communication among students to augment their engagement and active participation in blended courses.

5.3 Limitation and Further Study

The limitations of this study primarily lay in three aspects. Firstly, due to research constraints, it exclusively focused on five majors within the business field: Business Administration, Supply Chain Management, Human Resources Management, Financial Management, and Accounting. Consequently, it could have comprehensively represented all business majors. Secondly, only one private university was selected as the research subject in this study, resulting in a limited representation of the entire academic landscape. Thirdly, the model constructed in this paper incorporated only six potential variables that directly or indirectly influenced behavioral intention while omitting several additional variables previously found to exert substantial effects on behavioral intention from the conceptual framework. For further exploration, two perspectives could be considered: expanding the research scope to include other universities and incorporating more potential variables such as price values, habit, performance expectancy, and effort expectancy to support the construction of the research framework.

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