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Drivers of Attitude and Behavioral Intention Toward Blended Learning in Higher Education

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Abstract

Purpose: This research aims to investigate the Factors Impacting the Attitude and Behavioral Intention of Blended Learning in Higher Education in Chengdu, China. Blended learning involves integrating conventional in-person teaching with online distance education, and it has garnered growing interest and importance among educators and students in higher education institutions. **Research design, data, and methodology:** A quantitative approach was utilized for this study, with questionnaire surveys serving as the primary data collection tool. Before distributing the questionnaires, efforts were made to ensure content validity and reliability through item-objective consistency checks and pilot tests. Subsequently, confirmatory factor analysis (CFA) and structural equation modeling (SEM) were employed to examine the collected data comprehensively. By assessing model fit and confirming causal relationships between variables, hypothesis testing was conducted to draw scientifically sound conclusions. **Results:** Studies indicate that students' attitude towards blended learning and their perception of its usefulness significantly influence their intention to use blended learning. Furthermore, the theoretical model can forecast the behavioral intention of embracing blended learning within university settings. **Conclusions:** As a result, this research proposes encouraging students to recognize the usefulness of blended learning, fostering a favorable outlook on it, and prompting corresponding behavioral intention.

Keywords: Blended Learning, Higher Education, Attitude, Behavioral Intention, Chengdu

JEL Classification Code: E44, F31, F37, G15

1. Introduction

Online instruction involves using the Internet and modern information technology to facilitate teaching activities. This encompasses various formats, such as online courses, distance education, and digital learning materials, offering students more adaptable and convenient learning methods (Lotfizadeh & Acosta, 2023). Through online instruction, students can access knowledge anytime and anywhere while interacting and communicating with teachers and peers (Conrad, 2011). Blended learning involves integrating various educational approaches, technologies, and materials to address the diverse learning requirements of students (Kaban et al., 2024). This approach combines traditional classroom instruction, online learning, and hands-on projects to offer students a more comprehensive and tailored learning experience (Lv & Li, 2024). Additionally, blended learning fosters increased interaction and communication between educators and learners while positively impacting creativity and problem-solving skills (Latchem, 2010).

Blended education is a method of instruction that integrates traditional teaching with contemporary technological resources. Through this approach, students can learn using a combination of online classes, digital materials, and physical classrooms to gain a more comprehensive and diverse educational experience (Jones et al., 2007). Furthermore, blended education offers tailored learning

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paths and personalized resources to support individualized and effective study based on each student's unique characteristics and requirements. Additionally, educators can leverage data analysis and intelligent tools within blended education to monitor and assess students' progress while adjusting teaching strategies promptly for improved educational outcomes. As such, blended education encompasses various educational resources and tools while positively impacting aspects such as customization, efficiency, and interaction.

The benefits of blended learning are evident in numerous aspects. It can cater to the unique requirements of diverse learners and offers a wider range of flexible and varied learning approaches by integrating online and offline educational resources, enabling each student to discover a personalized learning path (Shoukat et al., 2024). Blended learning also enhances the effectiveness of information acquisition and knowledge exchange. By combining online platforms with physical classrooms, students can access essential information at any time and from anywhere and engage in interactions and communication with teachers and peers, thereby expediting the dissemination and sharing of knowledge (Suandi et al., 2024). Furthermore, blended learning can leverage various digital tools and smart devices to support the educational process effectively while enhancing the quality and efficiency of education (Rahmi et al., 2024). The challenges of blended learning primarily lie in areas such as incorporating teaching resources, teacher training, and course design. Firstly, ensuring seamless connectivity and complementarity among contents from various sources requires standardized integration standards and norms for teaching resources. Secondly, effective utilization of online and offline teaching tools and proficient organization of classroom activities necessitate specialized training and guidance for teachers in the blended learning model. Furthermore, balancing online and offline teaching content proportions while making adaptable adjustments based on real-world scenarios presents a challenge in course design (Safyari & Rezaei, 2024). Moreover, technical support also poses certain limitations, encompassing issues like network stability and device compatibility that could impact the efficacy of blended learning.

Due to the continuous advancement of information technology and the evolution of educational ideologies, many universities have started actively exploring the blended learning approach. This model combines traditional classroom instruction with online learning, offering students a more effective method of acquiring knowledge (Johnston & McCormack, 1996). Through blended learning, students can engage in real-time interaction and discussions during class while utilizing online resources for self-study and submitting assignments (White, 2000). This instructional approach not only enhances the quality of teacher-student interactions but also fosters independent thinking and problem-solving skills among students (Jones et al., 2007). Consequently, it is anticipated that more universities will opt for the blended learning model to align with the demands for educational reform in contemporary society.

Amid the COVID-19 pandemic, many higher education institutions actively embraced online courses and distance learning models to respond to the challenge. They developed virtual classroom platforms, created recorded lecture videos, and designed interactive online assignments, making online teaching the new standard. Additionally, there was an increased utilization of Massive Open Online Course (MOOC) platforms that offered free or paid courses in various professional fields (Liu, 2021). The COVID-19 outbreak has pushed higher education towards a more diverse, flexible, and digitalized direction while prompting global reflection and exploration of future strategies for adjusting to the hybrid learning model.

This study explores the factors influencing students' tendency to adopt blended learning behavioral intention. By analyzing elements like perceived usefulness, attitude, social influence, and facilitating conditions, it is clear that blended learning brings substantial benefits in meeting modern college students' diverse and personalized learning needs. It stimulates students' interest in knowledge and cultivates their independent learning abilities and innovative thinking, thereby better suiting future societal demands for talent development. This research result will provide critical theoretical support and practical guidance for promoting implementing the blended education model in higher education institutions.

2. Literature Review

2.1 Perceived Usefulness

Perceived usefulness pertains to whether an object or action holds practical value and importance for an individual or a collective (Davis, 1989). Perceived usefulness is an individual's mental process and assessment of specific information, abilities, or assets to ascertain if they can fulfill their requirements and yield positive outcomes (Vardar et al., 2024). Perceived usefulness is commonly understood as the level of convenience, enhancement in efficiency, and fulfillment of particular needs that users experience when utilizing a product (Zakaria et al., 2024). It allows users to play a crucial role in choosing and utilizing a specific system, accurately assessing its real value and relevance to themselves (Lin, 2007). It has become a significant factor in people's evaluation of mobile learning approaches (Ortiz-López et al., 2024). Increasing users' perceived usefulness of the Online Course Tool (WebCT) can also boost their positive attitude towards WebCT and motivate them to participate more willingly in related activities (Arteaga Sánchez et al., 2013). Based on these studies, the following hypothesis was proposed:

H1: Perceived usefulness has a significant impact on attitude.

H2: Perceived usefulness has a significant impact on behavioral intention.

2.2 Attitude

The attitude shown by users when using computer information systems refers to their positive behaviors and expectations (Davis, 1989). This concept involves preferences for information management systems and corresponding reactions of likes or dislikes (Asyari, 2024). Moreover, students' positive attitude towards computers as learning tools directly affects the formation of their intentions to use computers (Ocak & Karakuş, 2024). When making product choices, consumers consider their attitudes, which can be demonstrated through verbal expressions and usage decisions (Robey, 1979). Users with extensive computer operation experience will likely embrace new technologies and maintain a positive attitude.

Conversely, those needing more relevant experience or facing technical challenges may display a more positive outlook (Thi et al., 2023). In education, students' positive, supportive attitude towards online learning systems directly impacts their level of engagement and academic performance (Bag et al., 2020). Hence, the mindset of an individual plays a crucial role in shaping their behavioral intention when considering the adoption of a specific technology or service (Kara, 2020). Following the examination of these studies, a hypothesis was put forward:

H3: Attitude has a significant impact on behavioral intention.

2.3 Perceived Behavioral Control

Perceived behavioral control refers to an individual's belief in their ability to influence a specific behavior (Ajzen, 2002). It is a significant factor in influencing an individual's decision to adopt a particular behavior (Do et al., 2024). Encompassing their perception of the environment, self-assessment of abilities and resources, and expectations for achieving the goal (Zhang, 2024). In the context of participating in a particular activity, PBC can be used to analyze the potential barriers individuals may encounter while completing or participating in the activity (Ho et al., 2022). Perceived behavioral control is closely linked to behavioral intention during the implementation phase. Boosting an individual's confidence in their abilities and providing a supportive environment with positive incentives can facilitate the development of positive behavioral patterns (Aga, 2023). Therefore, perceived behavioral control is crucial in shaping people's intentions toward certain behaviors (Ajzen, 1991). After reviewing these studies, a hypothesis was proposed:

H4: Perceived behavioral control has a significant impact on behavioral intention.

2.4 Performance Expectancy

Performance expectancy refers to the anticipated performance targets and levels a technology is expected to attain in professional or academic settings (Venkatesh et al., 2003). It can also be seen as the projected result of an individual's or organization's actual performance on a specific task, project, or duty (Abd Aziz et al., 2021). The aim is to ensure that the product or technology can meet its intended objectives and deliver a positive user experience (Lutfie & Marcelino, 2020). Consequently, if blended learning has the potential to enhance students' academic performance, they are more likely to embrace this technology (Rudhumbu, 2022). With ChatGPT becoming more popular and advanced, more and more students are beginning to appreciate the convenience and benefits that the technology provides. Therefore, they are increasingly inclined to embrace these technologies to improve their academic performance actively (Duong et al., 2024). Performance expectancy represents a pivotal consideration for most individuals when embracing online education or other innovative educational approaches (Abd Aziz et al., 2023). As a result, perceived behavioral control has been demonstrated to significantly influence people's daily behaviors (Alajmi, 2012). Therefore, the following hypothesis is proposed:

H5: Performance expectancy has a significant impact on behavioral intention.

2.5 Effort Expectancy

Effort expectancy pertains to an individual's anticipation of the level of exertion needed to finish a specific undertaking (Yadav et al., 2016). Students hope they can easily learn, communicate, and share knowledge through ChatGPT without spending much time learning complicated operational steps or dealing with various technical issues (Duong et al., 2024). The effort expectancy is connected to the level at which students utilize video-based learning technologies, as opposed to their actual level of exertion (Abd Aziz et al., 2023). This is influenced by the ease of use of the utilized system; the blended learning model enables college students to reach their educational objectives effectively (Sang et al., 2023). Effort expectancy is closely associated with the perceived ease of utilizing e-learning technologies, and learners' direct utilization of these technologies will significantly impact their inclination toward them (Odelami et al., 2023). Per the UTAUT model, users' higher effort expectancy toward information technology will directly affect their behavioral intention (Neufeld et al., 2007). Therefore, the following assumption is made:

H6: Effort expectancy has a significant impact on behavioral intention.

2.6 Social Influence

Social influence refers to the impact of an individual's actions, beliefs, and values on users within a specific setting (Tarhini et al., 2017). Cava et al. (2023) emphasized that social influence is the extent to which influential individuals persuade consumers to adopt mobile Internet technology. Furthermore, Yunior and Augustine (2024) discovered that educators with social influence play a crucial role in the e-learning process by guiding students' acceptance and acknowledgment of new technologies. When choosing their type of social learning, influential figures in their lives often influence teenagers and choose their interests or types of social learning related to their future career plans (Cunningham et al., 2023). Consequently, when the guidance from others is more favorable, there is an increased likelihood of user adoption, which serves as a primary determinant of users' willingness to persist with this technology (Liang et al., 2024). This study found that students with higher social influence tend to be more inclined to participate in classroom discussions actively and demonstrate better e-learning willingness and academic performance (Billman et al., 2023). Based on the above studies, the following hypothesis is assumed:

H7: Social influence has a significant impact on behavioral intention.

2.7 Facilitating Conditions

Facilitating conditions pertain to whether a technology or system offers the necessary resources for users to facilitate task completion (Ebadi & Raygan, 2023). It also encompasses the user-friendliness and functionality of educational platforms or applications (Bervell & Arkorful, 2020). Users proficient in operating mobile phones or tablet computers may find it easier to adapt to the mobile learning environment and resolve encountered issues more efficiently (Camilleri & Camilleri, 2023). If these tools can provide intuitive, interactive, and diverse teaching resources with rich content, students will find using online classrooms more convenient and enjoyable (Wut et al., 2022). The flexibility and popularity of the e-learning system can foster student recommendations, thereby enhancing their intention to engage in e-learning (Koyu & Singh, 2024). Only by ensuring adequate resource support and usage experience can user needs be genuinely met, promoting the adoption of blended learning (Rudhumbu, 2022). Hence, facilitating conditions directly impact their willingness to opt for the mobile learning method (Waris & Hameed, 2023). Based on the above references, the following assumption can be derived:

H8: Facilitating conditions has a significant impact on behavioral intention.

2.8 Behavioral Intention

Behavioral intention refers to the tendency behavior exhibited by an individual in a specific situation, which can be revealed through observation and analysis (Davis, 1989). An in-depth understanding and analysis of behavioral intention is helpful for better understanding the needs and preferences of individuals or groups and is conducive to predicting possible future events or trends (Lv & Li, 2024). Various factors, including cognition, attitude, emotion, social influence, etc., influence behavioral intention formation. When predicting whether students will choose the blended learning mode, all the above factors must be comprehensively considered (Davis, 1989).

3. Research Methods and Materials

3.1 Research Framework

The proposed research model is based on the technology acceptance model (TAM), planned behavior theory (TPB), and Unified theory of technology acceptance and Use (UTAUT). TAM elucidates how perceived usefulness and attitude influence user behavioral intent.

This research model incorporates three established theoretical frameworks. The first framework, introduced by Davis (1989), examines the impact of perceived usefulness and attitude on behavioral intention. The second framework, developed by Ajzen (1991), explores the effect of perceived behavioral control on behavioral intention. The third framework, from a study by Venkatesh et al. (2003), investigates performance expectancy, effort expectancy, social influences, and facilitating conditions. The conceptual framework of the research is presented in Figure 1 below.

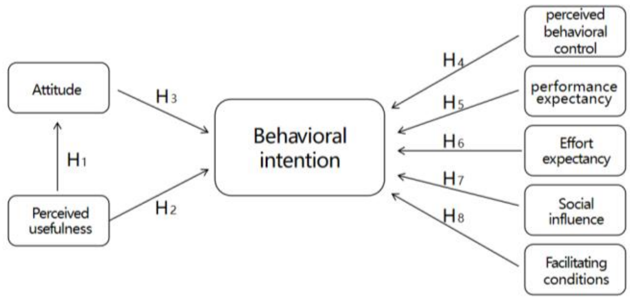

Figure 1: Research Conceptual Framework

H1: Perceived usefulness has a significant impact on attitude.
H2: Perceived usefulness has a significant impact on behavioral intention.
H3: Attitude has a significant impact on behavioral intention.
H4: Perceived behavioral control has a significant impact on behavioral intention.
H5: Performance expectancy has a significant impact on behavioral intention.
H6: Effort expectancy has a significant impact on behavioral intention.
H7: Social influence has a significant impact on behavioral intention.
H8: Facilitating conditions has a significant impact on behavioral intention.

3.2 Research Methodology

Based on the method combining empirical and quantitative analysis, this study collected sample data from sophomores, juniors, and seniors of undergraduate students in four universities in Chengdu using a questionnaire survey as the main tool. Before collecting large-scale data, we strictly verified the content validity and reliability of the questionnaire, including the item-objective congruence (IOC) test and Cronbach's Alpha pilot test. After the reliability test, we distributed the questionnaire online to the eligible respondent groups and ensured they had more than one year of blended learning experience.

The initial stage of this research involves conducting confirmatory factor analysis (CFA) using SPSS and AMOS to assess convergent validity. Throughout this process, we thoroughly explored and validated each construct in the conceptual model to ensure its alignment with real-world scenarios and reliability. The subsequent step entails employing structural equation modeling (SEM) to investigate the causal relationships between different constructs. SEM is a robust and adaptable statistical tool capable of testing intricate theories and structures while providing researchers with a comprehensive understanding of variable interrelationships, thereby unveiling the complexity and uncertainty inherent in these associations (Yurinanda et al., 2023).

3.3 Population and Sample Size

In this research, we chose undergraduate students from four universities in Chengdu, China, as the focal group. They needed at least one year of experience with blended learning to ensure they had a certain level of familiarity and interaction with this type of learning. According to Soper's (2006) SEM priori sample size calculator, at a significance level of 0.05 and considering eight latent variables and 30 observed variables, the recommended minimum sample size was 444. Therefore, for the actual study, we will distribute questionnaires and filter valid data from 500 responses for analysis.

3.4 Sampling Technique

The research utilized a multi-stage sampling approach, considering the unique characteristics and distinctions among various types of universities and disciplinary fields to ensure that the chosen samples accurately represented the university landscape in Chengdu. Initially, four diverse universities were selected as initial samples using judgment sampling. Then, specific sample sizes were determined for each university or sample stratum using stratified random sampling, adhering strictly to the selection criteria outlined in Table 1. This multi-stage sampling technique effectively mitigated potential biases and errors, enhancing the reliability and persuasiveness of the research findings.

Table 1: Sample Units and Sample Size

Universities	School Enrollments	Proportional Sample Size
Sichuan University	37000	170
Southwest Jiaotong University	28914	133
Chengdu University of Technology	20161	92
Sichuan University of Media and Communication	23000	105
Total	**109075**	**500**

Source: Constructed by author

4. Results and Discussion

4.1 Demographic Information

Based on the demographic data presented in Table 2, it is evident that out of the 500 respondents, there were 211 females and 289 males, constituting 42.2% and 57.8% of the total, respectively. Regarding grade distribution, sophomore students represented 25.2%, junior students accounted for 54.6%, and senior students comprised 20.2%. These statistics depict the distribution of respondents based on gender and academic year level.

Table 2: Demographic Profile

Demographic and General Data (N=500)		Frequency	Percentage
Gender	Male	289	57.8%
	Female	211	42.2%
Year of college	Sophomore	126	25.2%
	Junior	273	54.6%
	Senior	101	20.2%

4.2 Confirmatory Factor Analysis (CFA)

When conducting confirmatory factor analysis (CFA) to evaluate the test model's validity, various indicators must be considered. First, its reliability should be evaluated by considering factors like internal consistency and stability to ensure the measurement tool accurately reflects the concept or variable. Second, convergent validity must be assessed by examining the correlation between different measurement indicators to confirm their convergence to a common concept or dimension. Finally, discriminant validity also needs evaluation to determine the degree of differentiation between each measurement indicator and other unrelated constructs. Moreover, when using structural equation modeling (SEM) to examine causal relationships between structures, it is necessary to explore potential direct and indirect influence relationships among variables and validate model hypotheses through statistical methods (Crocker & Algina, 2006).

When the factor loading is 0.5 or higher, it indicates a strong correlation between the variable and the latent factor and is considered practical significance (Hair et al., 2019). The composite reliability (CR) is greater than 0.70 (Cheung et al., 2023). The average variance extracted (AVE) is greater than or equal to 0.4 (Sarstedt et al., 2017), and a Cronbach alpha (CA) value above 0.7 is considered good (Nunnally & Bernstein, 1994). In this research, the factor loadings for each item exceeded 0.50, ranging from 0.637 to 0.911. The CR value exceeded the level of 0.7. The AVE value exceeded 0.4, and the CA values all exceed 0.8. As indicated in the table 3 .

Table 3: Confirmatory Factor Analysis Result, Composite Reliability (CR) and Average Variance Extracted (AVE)

Variable	Source of Questionnaire (Measurement Indicator)	No.of Item	Cronbach's Alpha	Factors Loading	CR	AVE
Perceived Usefulness (PU)	Abdekhoda et al. (2019)	5	0.819	0.760-0.868	0.919	0.695
Attitude (ATT)	Dubey et al. (2023)	3	0.840	0.823-0.865	0.877	0.703
Behavioral Intention (BI)	Alrousan et al. (2022)	4	0.835	0.798-0.911	0.926	0.759
Effort Expectancy (EFE)	Rudhumbu (2022)	4	0.813	0.686-0.777	0.822	0.537
Performance Expectancy (PE)	Rudhumbu (2022)	4	0.828	0.663-0.704	0.782	0.473
Perceived Behavioral Control (PBC)	Al-Mamary et al. (2023)	3	0.815	0.637-0.755	0.747	0.497
Social Influence (SI)	Rudhumbu (2022)	3	0.828	0.696-0.856	0.832	0.624
Facilitating Conditions (FC)	Rudhumbu (2022)	4	0.819	0.664-0.799	0.806	0.511

Furthermore, Table 4 displayed various goodness-of-fit indices, including CMIN/DF, GFL, AGFI, NFI, CFI, TLI, and RMSEA. It is worth noting that all these values surpassed the acceptable standard range by a considerable margin. These results provide strong evidence for the adequacy of the measurement model's goodness of fit.

Table 4: Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	< 5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	1.354
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.936
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.921
RMSEA	< 0.08 (Pedroso et al., 2016)	0.027
NFI	≥ 0.80 (Wu & Wang, 2006)	0.940
CFI	≥ 0.80 (Bentler, 1990)	0.983
TLI	≥ 0.80 (Sharma et al., 2005)	0.981
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 means square error of approximation, NFI = Normed fit index, CFI = Comparative fit index, and TLI = Tucker-Lewis index

During the research data analysis, we carefully examined and assessed the discriminant validity presented in Table 5. The findings indicated that all variables were statistically significant, as their average variance extracted (AVE) values exceeded the inter-factor correlations.

Table 5: Discriminant Validity

	PU	ATT	BI	EFE	PE	PBC	SI	FC
PU	**0.833**							
ATT	0.591	**0.838**						
BI	0.539	0.533	**0.871**					
EFE	0.350	0.358	0.443	**0.732**				
PE	0.288	0.284	0.435	0.299	**0.687**			
PBC	0.285	0.302	0.413	0.299	0.284	**0.704**		
SI	0.395	0.354	0.483	0.326	0.350	0.284	**0.789**	
FC	0.360	0.384	0.483	0.430	0.407	0.389	0.328	**0.714**

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

4.3 Structural Equation Model (SEM)

This research analyzed the gathered data using the Structural Equation Model (SEM). In practical scenarios, SEM can examine the observed data and investigate potential causal relationships and mutual influences (Yurinanda et al., 2023). Furthermore, as the level of goodness-of-fit increases, it indicates that the established model aligns well with real data, demonstrating reasonable and positive correlations among variables. In contrast, a lower value may suggest potential negative correlations or other significant factors that have not been considered (Byrne, 2010). As depicted in Table 6, the statistical values are CMIN/DF = 2.566, GFI = 0.851, AGFI = 0.820, RMSEA = 0.056, NFI = 0.884, CFI = 0.925, and TLI = 0.916—all of which exceed acceptable thresholds—thus confirming the suitability of the model.

Table 6: Goodness of Fit for Structural Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	< 5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	2.566
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.851
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.820
RMSEA	< 0.08 (Pedroso et al., 2016)	0.056
NFI	≥ 0.80 (Wu & Wang, 2006)	0.884
CFI	≥ 0.80 (Bentler, 1990)	0.925
TLI	≥ 0.80 (Sharma et al., 2005)	0.916
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 means square error of approximation, NFI = Normed fit index, CFI = Comparative fit index, and TLI = Tucker-Lewis index

4.4 Research Hypothesis Testing Result

The regression coefficient measures the degree of the independent variable's influence on the dependent variable, while the standardized path coefficient can more clearly present the correlation intensity among various variables. As presented in Table 7 all eight hypotheses proposed in the study were supported. The behavioral intention to use blended learning was strongly influenced by social influence, followed by attitude, and attitude was strongly influenced by perceived usefulness.

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-value	Result
H1: PU→ATT	0.651	13.941*	Supported
H2: PU→BI	0.215	3.654*	Supported
H3: ATT→BI	0.236	3.912*	Supported
H4: PBC→BI	0.168	3.578*	Supported
H5: PE→BI	0.212	4.524*	Supported
H6: EFE→BI	0.177	3.941*	Supported
H7: SI→BI	0.250	5.611*	Supported
H8:FC→BI	0.180	3.989*	Supported

Note: *** $p<0.001$, ** $p<0.01$, * $p<0.05$
Source: Created by the author

The primary factor impacting attitudes is perceived usefulness. The standardized coefficient (β) for HI is 0.651 with a T-value of 13.941, which aligns with similar findings from previous research conducted by Yadav et al. (2016), Mafuna and Wadesango (2016), and Cheng (2022). When students think blended learning can solve problems on time and improve learning efficiency, they will be more inclined to adopt a positive attitude.

The perceived usefulness exerts a significant direct impact on behavioral intention, as evidenced by a standardized coefficient (β) of 0.215 and a T-value of 3.654 for H2, aligning with the findings of Shin and Kang (2015), Cheng (2012), Gupta (2020), and Thi et al. (2023). When students positively perceive the usefulness of blended learning, it will directly affect their intention to use this behavior.

Attitude has a notable direct influence on the behavioral intention to act, with the standard coefficient (β) of H3 at 0.236 and a T-value of 3.912. This aligns with the findings from studies by Chen et al. (2014), Buabeng-Andoh and Baah (2020), Alajmi (2012), and Dubey et al. (2023). A good attitude can usually stimulate the willingness to act positively, making students more willing to accept new concepts, try new methods, and have the courage to face challenges.

The perceived behavioral control exerts a significant direct influence on behavioral intention, with the normalization coefficient (β) for H4 being 0.168 and the T-value reaching 3.578. These findings align with previous research conducted by Ajzen (2002), Murugesan and Jayavelu (2015), Shih (2008), and Ohanu et al. (2022). Through perceived behavioral control, students can have a clearer understanding that they need to adopt blended learning to achieve the expected goals, thereby enhancing their ability to form and implement specific behavioral intentions.

Performance expectancy has a significant direct impact on behavioral intention. The standardization coefficient (β) of H5 is 0.212, and the T-value is 4.524. This finding aligns with the research outcomes reported by Neufeld et al. (2007), Onaolapo and Oyewole (2018), Lwoga and Komba (2015), and Lantu et al. (2023). When students clearly understand their performance goals and expectations, they are more inclined to actively take behavioral measures of blended learning to achieve their goals.

Effort expectancy has a significant direct impact on behavioral intention. The standardization coefficient (β) of H6 is 0.177, and the T-value is 3.941. This finding aligns with the research outcomes reported by Venkatesh et al. (2012), Sung et al. (2015), Thaker et al. (2022), and Tarhini et al. (2017). Students with positive expectations for their future grades usually focus more on blended learning and are willing to make extra efforts.

Social influence has a significant direct impact on behavioral intention. The standardization coefficient (β) of H6 is 0.250, and the T-value is 5.611. This finding aligns with the research outcomes reported by Neufeld et al. (2007), Lwoga and Komba (2015), Twum et al. (2022), and Bommer et al. (2022). Social influence acts on every individual and imperceptibly shapes their ideological concepts and behavioral intentions through various channels and ways.

The Facilitating conditions significantly impact behavioral intention. The standardization coefficient (β) of H6 is 0.180, and the T-value is 3.989. This finding aligns with the research outcomes reported by Chawla and Joshi (2020), Shah and Khanna (2023), and Reyes-Mercado et al. (2023). Specifically, many factors, such as the learning environment, convenience, and usage efficiency, may all affect a person's behavioral intention to varying degrees.

5. Conclusion and Recommendation

5.1 Conclusion

This study aims to comprehensively analyze the factors influencing attitudes and behavioral intentions toward using blended learning in higher education institutions in Chengdu, China. The conceptual framework put forward by researchers included eight hypotheses to investigate the factors that impact behavioral intention. Following the compilation and verification of questionnaire reliability, it was distributed online to undergraduates with over a year of blended learning experience in four universities in Chengdu. Utilizing the gathered data, CFA was utilized to assess and validate the research conceptual model's reliability. SEM was then used to analyze and discuss the influences on college students' attitudes and behavioral intentions toward using blended learning. The findings indicated that all eight proposed hypotheses were supported, successfully achieving the research objectives.

The results of this study can be summarized as follows:

First, the impact of perceived usefulness on attitude is the most significant. This is because people tend to evaluate whether a situation or product is useful to them before deciding whether to take action. When individuals perceive something as having practical value for themselves, they are more likely to form a positive attitude and support related behaviors. However, while attitude can influence willingness and inclination, it does not always directly translate into specific actions. Therefore, perceived usefulness is crucial in many cases, motivating people to take concrete actions.

Secondly, perceived behavioral control has a notable effect on behavioral intention. It involves understanding factors such as the environment, internal motivation, and external pressure and adjusting one's behavior accordingly. Research indicates that when individuals clearly understand their behavior and can effectively control it, this significantly influences the formation and implementation of specific behavioral intentions.

Lastly, performance expectancy, effort expectancy, social influence, and facilitating conditions all impact behavioral intention. Specifically, performance expectancy refers to an individual's anticipated task performance level; effort expectancy relates to the perceived amount of effort required to achieve a goal; social influence encompasses attitudes and opinions from others as well as group pressure; facilitating conditions refer to external environmental factors that can either promote or hinder certain actions taken by individuals. These aspects collectively shape individuals' choices and decisions when forming behavioral intentions through their interwoven effects.

5.2 Recommendation

In a study conducted by four universities in Chengdu, an extensive analysis was carried out to examine the impact of perceived usefulness (PU), perceived behavioral control (PBC), performance expectancy (PE), effort expectancy (EFE), social influence (SI), and facilitating conditions (FC) on attitudes (ATT) and behavioral intentions (BI) towards the use of blended learning. These factors are identified as crucial influencers in college students' adoption of blended learning and require further development and promotion.

The findings indicate that perceived usefulness strongly predicts attitudes toward using blended learning. Therefore, it is essential to promote and cultivate its practical application value when advocating for its adoption. When undergraduate students recognize that blended learning can enhance their academic performance, they are more inclined to embrace and actively apply this approach.

Furthermore, perceived behavioral control has been shown to help college students better understand the necessity of adopting blended learning to achieve their desired outcomes and effectively guide them toward taking appropriate actions. Additionally, performance expectancy, effort expectancy, social influence, and facilitating conditions collectively shape individual choices and decisions when forming behavioral intentions.

This research comprehensively elucidates the factors influencing college students' attitudes and intentions regarding blended learning. It emphasizes that these variables play significant guiding roles in project investment decisions and maximizing the utilization of the blended education model. These insights will contribute to better promoting and optimizing potential benefits arising from technological innovation combined with educational reform in the field of education in the future.

5.3 Limitation and Further Study

This study is subject to certain limitations. The following recommendations are proposed for further research. Firstly, the study focuses solely on four higher education institutions in Chengdu, limiting its scope and sample size. To achieve more comprehensive and representative data, future research should include a wider range of higher education institutions from different regions and of varying types and sizes. Secondly, there is potential for further exploration into the course content of blended learning beyond MOOCs and VR technology, including the introduction of emerging technologies such as artificial intelligence-assisted learning systems and personalized learning platforms, with an in-depth analysis of their roles in blended learning. Thirdly, expanding the survey subjects to include stakeholders such as parents, alums, and corporate employers alongside students and teachers would allow for comparing their evaluations of educational quality under the blended learning model. Lastly, improvements can be made to the methodology by adopting more rigorous experimental design methods to verify causal relationships while combining quantitative and qualitative analyses better to understand college students' behavioral intentions in blended learning.

References

Abd Aziz, N. N., Awang Kader, M. A. R., & Ab Halim, R. (2021). The impact of technostress on student satisfaction and performance expectancy. *Asian Journal of University Education, 17*(4), 538-552. https://doi.org/10.24191/ajue.v17i4.16466

Abd Aziz, N. N., Aziz, M. A., & Abd Rahman, N. A. S. (2023). The mediating effects of student satisfaction on technostress-performance expectancy relationship in university students. *Journal of Applied Research in Higher Education, 15*(1), 113-129. https://doi.org/10.1108/JARHE-03-2021-0117

Abdekhoda, M., Maserat, E., & Ranjbaran, F. (2019). A conceptual model of flipped classroom adoption in medical higher education. *Interactive Technology and Smart Education, 17*(4), 393-401. https://doi.org/10.1108/ITSE-09-2019-0058

Aga, M. K. (2023). The mediating role of perceived behavioral control in the relationship between entrepreneurship education and entrepreneurial intentions of university students in Ethiopia. *Journal of Innovation and Entrepreneurship: A Systems View Across Time and Space, 12*(1), 1-10. https://doi.org/10.1186/s13731-023-00297-w

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50*(2), 179-211. https://doi.org/10.1016/0749-5978(91)90020-T

Ajzen, I. (2002). Perceived behavioral control, self-efficacy, locus of control, and the theory of planned behavior. *Journal of Applied Social Psychology, 32*(4), 665-683. https://doi.org/10.1111/j.1559-1816.2002.tb00236.x

Alajmi, B. M. (2012). The intention to share: Psychological investigation of knowledge sharing behavior in online communities. *Journal of Information and Knowledge Management, 11*(3), 11-20. https://doi.org/10.1142/S0219649212500220

Al-Mamary, Y. H., & Shamsuddin, A. (2015). Testing of the technology acceptance model in context of Yemen. *Mediterranean Journal of Social Sciences, 6*(4S1), 268-273. https://doi.org/10.5901/mjss.2015.v6n4s1p268

Al-Mamary, Y. H. S., Siddiqui, M. A., Abdalraheem, S. G., Jazim, F., Abdulrab, M., Rashed, R. Q., Alquhaif, A., & Alhaji, A. A. (2023). Factors impacting Saudi students' intention to adopt learning management systems using the TPB and UTAUT integrated model. *Journal of Science and Technology Policy Management, 2*(3), 30-46. https://doi.org/10.1108/JSTPM-04-2022-0068

Alrousan, M. K., Madadha, A. A., Khasawneh, M. H. A., & Tweissi, A. A. (2022). Determinants of virtual classroom adoption in Jordan: The case of Princess Sumaya University for Technology. *Interactive Technology and Smart Education, 19*(2), 121-144. https://doi.org/10.1108/ITSE-09-2020-0211

Arteaga Sánchez, R., Duarte Hueros, A., & García Ordaz, M. (2013). E-learning and the University of Huelva: A study of WebCT and the technological acceptance model. *Campus-Wide Information Systems, 30*(2), 135-160. https://doi.org/10.1108/10650741311306318

Asyari, A. (2024). Students' perceptions and attitudes toward learning based on learning management system: A future recommendation on blended learning design. *Pegem Journal of Education and Instruction, 14*(2), 78-85. https://doi.org/10.47750/pegegog.14.02.09

Awang, Z. (2012). *Structural equation modeling using AMOS* (1st ed.). Penerbit Universiti Teknologi MARA.

Bag, S., Aich, P. B., & Islam, M. A. (2020). Behavioral intention of "digital natives" toward adapting the online education system in higher education. *Journal of Applied Research in Higher Education, 14*(1), 16-40. https://doi.org/10.1108/JARHE-08-2020-0278

Bentler, P. M. (1990). Comparative fit indexes in structural models. *Psychological Bulletin, 107*(2), 238-246. https://doi.org/10.1037/0033-2909.107.2.238

Bervell, B., & Arkorful, V. (2020). LMS-enabled blended learning utilization in distance tertiary education: Establishing the relationships among facilitating conditions, voluntariness of use, and use behaviour. *International Journal of Educational Technology in Higher Education, 17*, 1-16. https://doi.org/10.1186/s41239-020-0183-9

Billman, A., Surjandy, A., & Rumangkit, S. (2023). Analysis of positive emotional effects on student learning involvement, social influence, and effort expectations factors on academic achievement and use of e-learning systems. *2023 7th International Conference on New Media Studies (CONMEDIA),* 280-285. https://doi.org/10.1109/CONMEDIA60526.2023.10428400

Bommer, W. H., Rana, S., & Milevoj, E. (2022). A meta-analysis of eWallet adoption using the UTAUT model. *International Journal of Bank Marketing, 40*(4), 791-819. https://doi.org/10.1108/IJBM-06-2021-0258

Buabeng-Andoh, C., & Baah, C. (2020). Pre-service teachers' intention to use learning management system: An integration of UTAUT and TAM. *Interactive Technology and Smart Education, 17*(4), 455-474. https://doi.org/10.1108/ITSE-02-2020-0028

Byrne, B. M. (2010). *Structural equation modeling with AMOS* (2nd ed.). Taylor and Francis Group.

Camilleri, M. A., & Camilleri, A. C. (2023). Learning from anywhere, anytime: Utilitarian motivations and facilitating conditions for mobile learning. *Technology, Knowledge and Learning, 28*(4), 1687-1705. https://doi.org/10.1007/s10758-022-09608-8

Cava, L. L., Aiello, L. M., & Tagarelli, A. (2023). Drivers of social influence in the Twitter migration to Mastodon. *Scientific Reports, 13*(1), 1-12. https://doi.org/10.1038/s41598-023-48200-7

Chawla, D., & Joshi, H. (2020). The moderating role of gender and age in the adoption of mobile wallet. *Foresight, 22*(4), 483-504. https://doi.org/10.1108/FS-11-2019-0094

Chen, J. F., Cheng, W. K., & Huang, Y. M. (2014). Integrating ISSM into TAM to enhance digital library services: A case study of the Taiwan Digital Meta-Library. *The Electronic Library, 34*(1), 58-73. https://doi.org/10.1108/EL-01-2014-0016

Cheng, P. M. (2022). Can tasks and learning be balanced? A dual-pathway model of cloud-based e-learning continuance intention and performance outcomes. *Kybernetes, 51*(1), 210-240. https://doi.org/10.1108/K-07-2020-0440

Cheng, Y. M. (2012). Using the UTAUT: Effects of quality antecedents on e-learning acceptance. *Internet Research, 22*(3), 361-390. https://doi.org/10.1108/10662241211235699

Cheung, G. W., Cooper-Thomas, H. D., Lau, R. S., & Wang, L. C. (2023). Reporting reliability, convergent and discriminant validity with structural equation modeling: A review and best-practice recommendations. *Asia Pacific Journal of Management, 2*(1), 40-65. https://doi.org/10.1007/s10490-023-09871-y

Conrad, R.-M. (2011). *Engaging the online learner: Activities and resources for creative instruction* (1st ed.). Jossey-Bass.

Crocker, L., & Algina, J. (2006). *Introduction to classical and modern test theory* (1st ed.). Cengage Learning.

Cunningham, S. J., Hutchison, J., Ellis, N., Hezelyova, I., & Wood, L. A. (2023). The cost of social influence: Own-gender and gender-stereotype social learning biases in adolescents and adults. *PLoS ONE, 18*(8), 1-24. https://doi.org/10.1371/journal.pone.0290122

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319-340. http://www.jstor.org/stable/249008

Do, H. L., Vu, T. M. P., Nguyen, V. G., Vu, N. M., Nguyen, D. T., & Tran, T. V. (2024). The mediating role of perceived behavioral control on the relationship between financial knowledge and saving intention: A study of Vietnamese university students. *Human Behavior, Development & Society, 25*(1), 30-41. https://doi.org/10.62370/hbds.v25i1.270883

Dubey, P., Pradhan, R. L., & Sahu, K. K. (2023). Underlying factors of student engagement to e-learning. *Journal of Research in Innovative, 16*(1), 17-36. https://doi.org/10.1108/JRIT-09-2022-0058

Duong, C. D., Bui, D. T., Pham, H. T., Vu, A. T., & Nguyen, V. H. (2024). How effort expectancy and performance expectancy interact to trigger higher education students' uses of ChatGPT for learning. *Interactive Technology and Smart Education, 21*(3), 356-380. https://doi.org/10.1108/ITSE-05-2023-0096

Ebadi, S., & Raygan, A. (2023). Investigating the facilitating conditions, perceived ease of use and usefulness of mobile-assisted language learning. *Smart Learning Environments, 10*(1), 1-12. https://doi.org/10.1186/s40561-023-00250-0

Gupta, K. P. (2020). Investigating the adoption of MOOCs in a developing country: Application of technology-user-environment framework and self-determination theory. *Interactive Technology and Smart Education, 17*(4), 355-375. https://doi.org/10.1108/ITSE-06-2019-0033

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate data analysis* (8th ed.). Cengage Learning.

Ho, S. S., Goh, T. J., & Chuah, A. S. F. (2022). Perceived behavioral control as a moderator: Scientists' attitude, norms, and willingness to engage the public. *PLoS ONE, 17*(10), 1-24. https://doi.org/10.1371/journal.pone.0275643

Johnston, S., & McCormack, C. (1996, January 1). Integrating information technology into university teaching: Identifying the needs and providing the support. *International Journal of Educational Management, 10*(5), 36-42.

Jones, P., Jones, A., Packham, G., Thomas, B., & Miller, C. (2007). It's all in the mix: The evolution of a blended e-learning model for an undergraduate degree. *Journal of Systems and Information Technology, 9*(2), 124-142. https://doi.org/10.1108/13287260710839210

Kaban, A. L., Yataganbaba, E., Cobanoglu, A. A., & Kokoc, M. (2024). Teachers' readiness for blended learning, their reasons, challenges, and suggestions for practising blended learning. *Turkish Online Journal of Distance Education, 25*(2), 157-173.

Kara, S. (2020). Prospective visual arts teachers' innovation skills and attitudes towards computer-assisted instruction. *International Journal of Technology in Education and Science, 4*(2), 98-107. https://files.eric.ed.gov/fulltext/EJ1255560.pdf

Koyu, B., & Singh, R. J. (2024). Predicting the intention to use an e-learning module on climate-smart horticulture. *Current Science, 126*(4), 478-485.

Lantu, D. C., Labdhagati, H., & Dewanto, I. (2023). Workplace e-learning acceptance: Combining symmetrical and asymmetrical perspectives. *Journal of Workplace Learning, 35*(4), 341-358. https://doi.org/10.1108/JWL-08-2021-0109

Latchem, C. R. (2010). *Distance and blended learning in Asia* (1st ed.). Routledge.

Liang, S. Z., Xu, J. L., & Huang, E. (2024). Comprehensive analysis of the effect of social influence and brand image on purchase intention. *SAGE Open, 14*(1), 1-13. https://doi.org/10.1177/21582440231218771

Lin, H. F. (2007). The role of online and offline features in sustaining virtual communities: An empirical study. *Internet Research, 17*(2), 119-138. https://doi.org/10.1108/10662240710736997

Liu, C. H. (2021). The adoption of e-learning beyond MOOCs for higher education. *International Journal of Accounting & Information Management, 29*(2), 217-227. https://doi.org/10.1108/IJAIM-08-2020-0129

Lotfizadeh, A. D., & Acosta, G. (2023). Evaluation of a reinforcement contingency to increase university students' webcam usage during online classroom instructions. *Journal of Behavioral Education, 32*(4), 803-813. https://doi.org/10.1007/s10864-022-09474-5

Lutfie, H., & Marcelino, D. (2020). Investigating Facebook advertising feature through performance expectancy on customer purchase intention. *2020 8th International Conference on Cyber and IT Service Management (CITSM),* 1-7. https://doi.org/10.1109/CITSM50537.2020.9268905

Lv, N., & Li, Z. G. (2024). The effects of blended learning environment on college students' learning effectiveness: Exploring the role of behavioral intentions and self-efficacy through the UTAUT2 model. *SAGE Open, 14*(2), 1-14. https://doi.org/10.1177/21582440241251604

Lwoga, E. T., & Komba, M. (2015). Antecedents of continued usage intentions of web-based learning management system in Tanzania. *Education + Training, 57*(7), 738-756. https://doi.org/10.1108/ET-02-2014-0014

Mafuna, L., & Wadesango, N. (2016). Exploring lecturers' acceptance level of learning management system (LMS) applying the extended technology acceptance model (TAM). *Journal of Social Sciences, 48*(2), 63-70. https://doi.org/10.1080/09718923.2016.11893571

Murugesan, R., & Jayavelu, R. (2015). Testing the impact of entrepreneurship education on business, engineering, and arts and science students using the theory of planned behavior. *Journal of Entrepreneurship in Emerging Economies, 7*(3), 256-275. https://doi.org/10.1108/JEEE-12-2014-0053

Neufeld, D., Dong, L. Y., & Higgins, C. (2007). Charismatic leadership and user acceptance of information technology. *European Journal of Information Systems, 16,* 494-510. https://doi.org/10.1057/palgrave.ejis.3000682

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

Ocak, G., & Karakuş, G. (2024). Measuring change in undergraduate students' attitudes towards online exams depending on gender and some technological variables. *Malaysian Online Journal of Educational Technology, 12*(1), 1-14. https://doi.org/10.52380/mojet.2024.12.1.427

Odelami, B., Folorunso, O., & Igbinovia, M. O. (2023). Perception of external control, effort expectancy and use of electronic information resources by undergraduates in selected universities in Nigeria. *Library Philosophy & Practice, 1,* 1-19.

Ohanu, I. B., Shodipe, T. O., Ohanu, C. M. G., & Okeakwa, J. E. A. (2022). Quality blended learning systems for improving undergraduate students' skills. *Quality Assurance in Education, 30*(2), 169-183.

Onaolapo, S., & Oyewole, O. (2018). Performance expectancy, effort expectancy, and facilitating conditions as factors influencing smartphones use for mobile learning by postgraduate students of the University of Ibadan, Nigeria. *Interdisciplinary Journal of e-Skills and Lifelong Learning, 14,* 95-115. https://doi.org/10.28945/4085

Ortiz-López, A., Sánchez-Prieto, J. C., & Olmos-Migueláñez, S. (2024). Perceived usefulness of mobile devices in assessment: A comparative study of three technology acceptance models using PLS-SEM. *Journal of New Approaches in Educational Research, 13*(1), 1-12. https://doi.org/10.1007/s44322-023-00001-6

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

Rahmi, U., Fajri, B. R., & Azrul, A. (2024). Effectiveness of interactive content with H5P for Moodle-Learning Management System in blended learning. *Journal of Learning for Development, 11*(1), 66-81. https://doi.org/10.56059/jl4d.v11i1.1135

Reyes-Mercado, P., Barajas-Portas, K., Kasuma, J., Almonacid-Duran, M., & Zamacona-Aboumrad, G. A. (2023). Adoption of digital learning environments during the COVID-19 pandemic: Merging technology readiness index and UTAUT model. *Journal of International Education in Business, 16*(1), 91-114. https://doi.org/10.1108/JIEB-10-2021-0097

Robey, D. (1979). User attitudes and management information system use. *The Academy of Management Journal, 22*(3), 527-538. https://www.jstor.org/stable/255742

Rudhumbu, N. (2022). Applying the UTAUT2 to predict the acceptance of blended learning by university students. *Asian Association of Open Universities Journal, 17*(1), 15-36. https://doi.org/10.1108/AAOUJ-08-2021-0084

Safyari, S., & Rezaei, E. (2024). Identifying the criteria for techno-pedagogical competencies of faculty members in blended learning implementation: A review. *Interdisciplinary Journal of Virtual Learning in Medical Sciences, 15*(1), 18-32. https://doi.org/10.30476/IJVLMS.2024.99591.1248

Sang, G., Wang, K., Li, S., Xi, J., & Yang, D. (2023). Effort expectancy mediates the relationship between instructors' digital competence and their work engagement: Evidence from universities in China. *Educational Technology Research and Development: A Bi-Monthly Publication of the Association for Educational Communications & Technology, 71*(1), 99-115. https://doi.org/10.1007/s11423-023-10205-4

Sarstedt, M., Ringle, C. M., & Hair, J. F. (2017). Partial Least Squares Structural Equation Modeling. In C. Homburg, M. Klarmann, & A. Vomberg (Eds.), *Handbook of Market Research* (pp. 1-40). Springer. https://doi.org/10.1007/978-3-319-05542-8_15-1

Shah, J., & Khanna, M. (2023). Determining the post-adoptive intention of millennials for MOOCs: An information systems perspective. *Information Discovery and Delivery, 6*(4), 1-10. https://doi.org/10.1108/IDD-11-2022-0109

Sharma, G. P., Verma, R. C., & Pathare, P. (2005). Mathematical modeling of infrared radiation thin layer drying of onion slices. *Journal of Food Engineering, 71*(3), 282-286. https://doi.org/10.1016/j.jfoodeng.2005.02.010

Shih, H. P. (2008). Using a cognition-motivation-control view to assess the adoption intention for web-based learning. *Computers & Education, 50*(3), 327-337. https://doi.org/10.1016/j.compedu.2006.06.001

Shin, W. S., & Kang, M. (2015). The use of a mobile learning management system at an online university and its effect on learning satisfaction and achievement. *International Review of Research in Open Distributed Learning, 16*(3), 110-130. https://doi.org/10.19173/irrodl.v16i3.1984

Shoukat, R., Ismayil, I., Huang, Q., Oubibi, M., Younas, M., & Munir, R. (2024). A comparative analysis of blended learning and traditional instruction: Effects on academic motivation and learning outcomes. *PLoS ONE, 19*(3), 1-18. https://doi.org/10.1371/journal.pone.0298220

Sica, C., & Ghisi, M. (2007). The Italian versions of the Beck Anxiety Inventory and the Beck Depression Inventory-II: Psychometric properties and discriminant power. In M. A. Lange (Ed.), *Leading-Edge Psychological Tests and Testing Research* (pp. 27-50). Nova.

Soper, D. (2006). *Calculator: A-priori sample size for structural equation models. Daniel Soper.* https://www.danielsoper.com/statcalc/calculator.aspx?id=89

Suandi, I. K., Santyasa, I. W., Tegeh, I. M., & Sudarma, I. K. (2024). The effect of problem-based blended learning and learning autonomy on students' learning outcomes in accounting. *Conhecimento & Diversidade, 16*(41), 474-491. https://doi.org/10.18316/rcd.v16i41.11512

Sung, H. N., Jeong, D. Y., Jeong, Y. S., & Shin, J. I. (2015). The relationship among self-efficacy, social influence, performance expectancy, effort expectancy, and behavioral intention in mobile learning service. *International Journal of u-and e-Service, Science and Technology, 8*(9), 197-206. https://doi.org/10.14257/ijunesst.2015.8.9.21

Tarhini, A., Masa' deh, R., 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

Thaker, H. M. T., Thaker, M. A. M. T., Khaliq, A., Pitchay, A. A., & Hussain, H. I. (2022). Behavioural intention and adoption of internet banking among clients of Islamic banks in Malaysia: An analysis using UTAUT2. *Journal of Islamic Marketing, 13*(5), 1171-1197. https://doi.org/10.1108/JIMA-11-2019-0228

Thi, H. P., Tran, Q. N., La, L. G., Doan, H. M., & Vu, T. D. (2023). Factors motivating students' intention to accept online learning in emerging countries: The case study of Vietnam. *Journal of Applied Research in Higher Education, 15*(2), 324-341. https://doi.org/10.1108/JARHE-05-2021-0191

Twum, K. K., Ofori, D., Keney, G., & Yeboah, B. K. (2022). Using the UTAUT, personal innovativeness and perceived financial cost to examine students' intention to use e-learning. *Journal of Science and Technology Policy Management, 13*(3), 713-737. https://doi.org/10.1108/JSTPM-12-2020-0168

Vardar, N., Gümüs, Ç., & Gündüz, M. A. (2024). Perceived usefulness, ease of use, and usage of distance education systems: Evidence from Turkey. *Turkish Online Journal of Educational Technology - TOJET, 23*(2), 93-99.

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. http://www.jstor.org/stable/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. *Journal of MIS Quarterly, 36*(1), 157-178.

Waris, I., & Hameed, I. (2023). Modeling teachers' acceptance of learning management system in higher education during COVID-19 pandemic: A developing country perspective. *Journal of Public Affairs, 23*(1), 1-13. https://doi.org/10.1002/pa.2821

White, S. (2000). Quality assurance and learning technologies: intersecting agendas in UK higher education. *Quality Assurance in Education, 8*(1), 7-15.

Wu, J. H., & Wang, Y. M. (2006). Measuring KMS success: A respecification of the DeLone and McLean's model. *Information and Management, 43*(6), 728-739. https://doi.org/10.1016/j.im.2006.05.002

Wut, T. M., Lee, S. W., & Xu, J. (2022). How do facilitating conditions influence student-to-student interaction within an online learning platform? A new typology of the serial mediation model. *Education Sciences, 12*(5), 12-34. https://doi.org/10.3390/educsci12050337

Yadav, R., Sharma, S. K., & Tarhini, A. (2016). A multi-analytical approach to understand and predict the mobile commerce adoption. *Journal of Enterprise Information Management, 29*(2), 222-237. http://dx.doi.org/10.1108/JEIM-04-2015-0034

Yunior, M. C., & Augustine, Y. (2024). The influence of social influence, relative advantage, user satisfaction on cloud-based e-learning with behavioral intention as a mediating variable. *Technium Social Sciences Journal, 56*, 36-50. https://doi.org/10.47577/tssj.v56i1.10742

Yurinanda, S., Rozi, S., & Sarmada, S. (2023). Analisis model kepuasaan civitas akademika terhadap pelayanan perpustakaan di Fakultas Sains dan Teknologi Universitas Jambi dengan metode Structural Equation Modeling (SEM). *Jurnal Lebesgue, 4*(3), 1532-1542. https://doi.org/10.46306/lb.v4i3.434

Zakaria, D. L., Maulana, D., & Agustina, S. (2024). The role of user-generated content on purchase intention with mediation of perceived usefulness and perceived trust. *Indonesian Journal of Advanced Research (IJAR, 3*(6), 743-760. https://doi.org/10.55927/ijar.v3i6.9795

Zhang, Y. (2024). Academic cheating as planned behavior: The effects of perceived behavioral control and individualism-collectivism orientations. *Higher Education: The International Journal of Higher Education Research, 87*(3), 567-590. https://doi.org/10.1007/s10734-023-01024-w