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Exploring College Students' Satisfaction in Cloud-Based Electronic Learning in Chengdu, China

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Abstract

Purpose: This study aims to explore the factors impacting college students' perceived usefulness, cognitive absorption, and satisfaction in cloud-based electronic learning in Chengdu, China. **Research design, data, and methodology:** Purposive, quota, and convenience Sampling were adopted. The quantitative method was used to collect sample data through a questionnaire survey. The sample consisted of students from four universities in Chengdu. Before data collection, Item-Objective Congruence (IOC) and a pilot test of Cronbach's Alpha were adopted to test the content validity and reliability. After data collection, Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM) were used to analyze the data to verify the reliability, validity, and goodness of fit of the data and to test the hypothesis. **Results**: Perceived usefulness was significantly impacted by interactivity, and cognitive absorption was significantly impacted by confirmation. Perceived usefulness was the strongest predictor of satisfaction, followed by perceived usefulness, cognitive absorption, and system quality. **Conclusions:** Six of the eight hypotheses proposed were supported and proved to be able to achieve the research objectives. Therefore, it is recommended that developers and universities ensure the interactivity, confirmation, and information quality of cloud-based e-learning systems so that students have a positive experience, thereby improving perceived usefulness, cognitive absorption, and satisfaction.

Keywords : Cloud-based e-learning, College students, Perceived usefulness, Cognitive absorption, Satisfaction

JEL Classification Code: E44, F31, F37, G15

1. Introduction

As society advances and technology evolves, education undergoes constant innovation and transformation to meet the shifting societal demands. The expansive development of science and technology and the progress of social informatization are major contributors to reform education methods. Along with the lightning development of IT, the education industry has ushered in the E era. In the globalized, informational, and networked knowledge economy age, e-learning plays an increasingly evident part in education (Zhao & Liu, 2009).

Electronic-learning learning utilizes modern Information and Communication Technology (ICT), combining Information Technology (IT) and courses to realize a be able to be reflected adequately put the student as the focus of a new study way, fully changing the conventional teaching scheme and educational nature, cultivating abundant high-quality talents of the perfect studying surrounding (Ma et al., 2008). The distinctive characteristics of e-learning, such as rich multimedia resources, convenient and fast harmonization and communication, and amicable mutual engagement, make it have a huge impact on the globe from the day of its emergence. Contrasted with traditional education and training, e-learning has significant advantages in terms of cost reduction, shortened timeframe, and enhanced effectiveness (Zhao & Liu, 2009). Because of its flexibility, e-learning exerts a significant social efficacy, promoting all social populations' acceptance of education (Meskhi et al., 2019).

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The Scholar: Human Sciences

In higher education, the obvious advantages of e-learning are mainly reflected in economizing studying time and costs, the studying patterns are very flexible and accessible, easy implementation of textbooks, the education procedure is transparent, and the data used for analysis can be quickly obtained. In addition, based on the illogical properties of special approaches, the formation of the students in the appropriate place and time perception capability of needful information is important (Meskhi et al., 2019). More and more students favor this flexible way of learning. China has developed plans for the development of education informatization. China's Education and Research Network has become the second largest network, connecting over 700 colleges, universities, research institutions, and over 140 cities. The user scale has reached over four million, and an interactional modern e-learning educational system has been preliminarily built up and came into being a digital educational circumstance that adapts to the evolution of education in the new age (Zhao & Liu, 2009).

In recent years, the emergence of cloud computing as a developed technology has brought new ideas to the education sector. Cloud-based e-learning is the transfer of cloud computing technology to the e-learning sector. Compared to traditional e-learning systems, cloud-based e-learning systems demonstrate superior adaptability and scalability. Cloud-based e-learning utilizes cloud computing technology in the e-learning sector, the tomorrow of basic e-learning facilities. Through the introduction of cloud computing, various organizations have access to singleness cloud-based e-learning that purveyors supply. Cloud-based e-learning opens up new avenues and effectively replaces traditional e-learning technologies. Many educational institutions have also recognized its huge potential value.

According to the Ministry of Education's Ten-year Development Plan for Education Informatization (2011-2020), the construction of a digital campus is an important part of the development strategy of education informatization. The cloud-based digital campus network has a cloud service platform with rich functions, which will play an important role in the construction of a digital campus. Given the widespread adoption and importance of cloud-based e-learning in higher education institutions, understanding factors impacting students' perceived usefulness, cognitive absorption, and satisfaction with cloud-based e-learning is necessary. Thus, this study aims to investigate and analyze the determinant factors Impacting college students' perceived usefulness, cognitive absorption, and satisfaction in cloud-based electronic learning in Chengdu, China.

2. Literature Review

2.1 Interactivity

Interactivity appertains to the level at which someone who takes part in the activity can control reciprocal discussion and role exchange during communication (Williams et al., 1988); in other words, it is defined as a communicative process that presents network users with control power and allows them to communicate with each other (Barreda et al., 2016). Steuer (1992) argues that interactivity refers to the ability to react to the external environment, demonstrated in the interaction between people and their environment. Thus, human reactions in contact with others, machines, media, or IT are all interactivity.

In the hypermedia computer-mediated communication environment, interactivity is one of the features of the website substance element, referring to the degree of responsiveness users create when scanning or manipulating the website (Hoffman & Novak, 1996). According to Gottardo and De Martino (2020), interactivity is "an open-ended operational intervention plan that problematically motivates learners to find resolvents stemming from prior knowledge." Hence, below hypotheses are indicated:

H1: Interactivity has a significant impact on perceived usefulness.

H3: Interactivity has a significant impact on satisfaction.

2.2 Confirmation

Confirmation refers to the degree to which the practical usage perception confirms the user's incipient anticipations (Oghuma et al., 2016). Confirmation, according to Bhattacherjee (2001), signifies the degree to which users perceive agreement between IS/IT use anticipation and their practical manifestation. In the e-learning system, confirmation is framed as the users' evaluation of an e-learning system (Bhattacherjee, 2001). Confirmation refers to comparing a product or service's perceived usefulness and practical usefulness (Bhattacherjee, 2001). In ECM, students foremost shape preliminary anticipations about the e-learning system and verify their anticipations after initially engaging (Xu et al., 2022). Oliver (1980) also believed that users would shape pre-use anticipations for products and perceive the function of the product based on practical use. Confirmation is formed by comparing the function of products with their initial anticipations. Hence, below hypotheses are indicated:

H2: Confirmation has a significant impact on cognitive absorption.

H5: Confirmation has a significant impact on satisfaction.

The Scholar: Human Sciences

2.3 Perceived Usefulness

Perceived usefulness is considered "a person's degree of recognition that his/her job performance will be enhanced by the use of a particular system" (Davis, 1989). It refers to the expected benefits of using IS/IT that users perceive (Bhattacherjee, 2001). Davis et al. (1989) argues that, in the TAM, PU is one of the main faiths that explain the user imbibe of a particular system pattern.

Perceived usefulness can be assessed by the speed with which the activity is completed, the amount of learning, the amount of knowledge in practice they gained, and the overall sense of usefulness (Candra & Jeselin, 2022). On the Internet, perceived usefulness is considered the personal's trust in the fictitious environment, the belief that using a fictitious environment can obtain information and services and improve personal performance through ideological exchange (Lin, 2007). Satisfaction with online instruction during COVID-19. Hence, below hypothesis is indicated:

H4: Perceived usefulness has a significant impact on satisfaction.

2.4 Cognitive Absorption

Cognitive absorption refers to the "deep state of participating in the software" (Agarwal & Karahanna, 2000); it is anchored in the field of psychology, on behalf of the personnel to the depth of the IS/IT participated in or the state of the whole experience (Leong, 2011; Reychav & Wu, 2015). Cognitive absorption is the level of engagement with an IT system (Guinaliu-Blasco et al., 2019) by which the overall technology user experience can be captured (Mpinganjira, 2019). Cognitive absorption reflects high participation and absorbing experience will lead to deep concern over the use of IS/IT, a state of deep engagement, is often considered a strong intrinsic motivation factor (Agarwal & Karahanna, 2000; Reychav & Wu, 2015; Saadé & Bahli, 2005). Cognitive absorption refers to time separation, focused immersion, high enjoyment, control, and curiosity, five sub-concepts of the multi-dimensional structures (Agarwal & Karahanna, 2000). Cognitive absorption embodies a mindset propelled by the user's intrinsic motivation associated with IS/IT while exhibiting high attention engagement and engaging experiences (Cheng, 2022; Reychav & Wu, 2015).

H6: Cognitive absorption has a significant impact on satisfaction.

2.5 Information Quality

Information quality pertains to the degree to which users consider information as pertinent, current, correct, and complete (Lee et al., 2007). Information quality is measured in terms of how accurate, complete, disseminated, efficient, relevant, comprehensive, and timely the information is referring to the quality of both the content and presentation of the reports produced from the information system (Ahn et al., 2007; Bailey & Pearson, 1983; DeLone & McLean, 1992; Srinivasan, 1985). IQ is the quality of the system produced (Tariq et al., 2018). In addition, Ahn et al. (2007) believe that high-level information quality increases the gaming experience for users.

In e-learning, the quality of curriculum content (Lee, 2006; Lee et al., 2009) and the quality of the curriculum design (Liu et al., 2010) are the main information quality measures. Wang et al. (2007) give all kinds of methods for valid information quality, such as accurate, up-to-date, and appropriate information should be provided by e-learning systems in due course, that should not only correlate to the work environment but also be easily understood and learned. Hence, below hypothesis is indicated:

H7: Information quality has a significant impact on satisfaction.

2.6 System Quality

System quality is the functional quality of the IS/IT per se (DeLone & McLean, 2003; Lin, 2007), meaning the exactness of the IS/IT function, convenience, potency, adaptability, dependability, safety, and reactivity (DeLone & McLean, 2003; Kim et al., 2008). System quality is decided by the user requirements that are defined during the analysis and development of the system, and Chen (2010) pointed out that it is the standard to measure the information processing systems themselves. In e-learning environment, system quality is defined as the learner with their e-learning system ability interplay quality perception of the degree (Chen, 2012; Cho et al., 2009; Pituch & Lee, 2006), which is a critical awareness and is used to identify whether students can easily learn course content through the function of e-learning system interaction.

When users find that IS/IT is a system with consistent quality is good and reliable, they will think that IS/IT is very well suited to their assignments (Chung et al., 2015); in addition, the premise of a high degree of match between users' perception of IS/IT and their assignments is that they find IS/IT can through the use of mobile equipment easily and seamlessly access, retrieval, and even send and receive files to the appropriate destination (Tam & Oliveira, 2016). Hence, below hypothesis is indicated:

H8: System quality has a significant impact on satisfaction.

The Scholar: Human Sciences

2.7 Satisfaction

Satisfaction means a state of mind or a state of emotion associated with and arises from an assessment of cognition of expected achievement differences (Bhattacherjee, 2001). Oliver (1980) stated that satisfaction means the valuation and sentimental reaction of an individual's whole experience based on a provision or product. Satisfaction could be characterized as a person's belief that some experience can arouse the active percepts of degree (Rust & Oliver, 1994). Shneiderman (2010) characterized user satisfaction as the users' response to enhancing skills or knowledge while utilizing a specific e-learning system.

Bokhari (2001) pointed out that satisfaction is a vehicle to verify the level of the e-learning system's fulfillment of users' demands and needs and enhance satisfaction according to the results. Many studies support user satisfaction as an important indicator for measuring e-learning system success (Samarasinghe, 2012). Chiu et al. (2007) believe that user feeling, functionality, and avail to end users can measure the user's satisfaction.

3. Research Methods and Materials

3.1 Research Framework

The conceptual framework provides research ideas for this study, establishes the study's range, defines the relevant variables, and describes the possible relationships between them. The conceptual framework in Figure 1 shows all the variables in this study and their relationships. It uses this as a road map to analyze the factors impacting college students' perceived usefulness, cognitive absorption, and satisfaction in cloud-based e-learning in Chengdu, China.

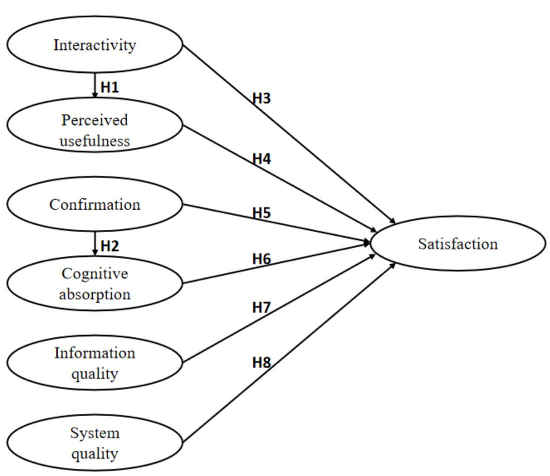

Figure 1: Conceptual Framework

H1: Interactivity has a significant impact on perceived usefulness.
H2: Confirmation has a significant impact on cognitive absorption.
H3: Interactivity has a significant impact on satisfaction.
H4: Perceived usefulness has a significant impact on satisfaction.
H5: Confirmation has a significant impact on satisfaction.
H6: Cognitive absorption has a significant impact on satisfaction.
H7: Information quality has a significant impact on satisfaction.
H8: System quality has a significant impact on satisfaction.

3.2 Research Methodology

This research explores the perceived usefulness, cognitive absorption, and satisfaction of cloud-based e-learning among students from four universities in Chengdu, China. Using empirical and quantitative analysis, the target population and sample size of 500 students with cloud-based e-learning experience were selected from four universities in Chengdu. In this research, a questionnaire survey was conducted to gather sample data, and questionnaires were made online by Questionnaire Star so that data could be distributed and collected conveniently and quickly. There are several steps in the sampling technique: purposive, quota and convenience sampling.

The IOC was used to confirm the validity of the content using expert rating results before distributing the questionnaire to the target population. To guarantee the reliability of the data, a pilot test of the reliability was conducted with 30 participants using Cronbach's alpha. Three experts assessed the IOC, with all metrics exceeding the acceptable threshold of 0.6. Cronbach's alpha reliability was utilized in a pilot test with 50 participants. In accordance with the standards set by Tavakol and Dennick (2011), a measurement tool is deemed suitable for use when the Alpha coefficient attains 0.70 or higher.

The questionnaire design consisted of three parts: screening questions, demographic information, and scale items, and it was distributed to 500 participants. CFA was adopted to verify the convergent validity, discriminant validity, and goodness-of-fit indices. SEM was applied to verify the significance relationship and test the hypothesis.

3.3 Population and Sample Size

Barnsbee et al. (2018) pointed out through their study that the target population is a combination of individuals whose conclusions can be drawn through interventional studies. It is a set of integral research units. The researchers tested their corollaries based on data from such a set of units. The result

Scholar: Human Sciences

of the study can be summarized as this set of units of some common features (Lavrakas, 2008). This study targeted university students from Chengdu, China, who had at least one semester of e-learning experience. Factors impacting perceived usefulness, cognitive absorption, and satisfaction with cloud-based e-learning in this population will be studied.

The sample size is critical for planning experiments, both the major experiment and any preliminary experiment. The sample size was calculated to clinch the minimum quantity of respondents required in the experiment (Whitehead et al., 2015).

To get efficient statistical results, the researchers collected 500 samples from four universities in Chengdu, according to the recommended minimum sample size. Therefore, this study will take 500 undergraduates and postgraduates from four universities in Chengdu as a sample for research.

3.4 Sampling Technique

In an effort to help respondents correctly answer the studied questions and smoothly carry out the research program, researchers use binding sampling techniques and sampling procedure selection (Palinkas et al., 2015).

This study employed the stage-by-stage sampling procedure combined with a non-probability sampling techniques approach to sample the research objects to ensure that the dataset meets the study's objectives. This study divides the sampling process into three stages. In the first stage, researchers chose the purposive sampling method and selected four universities in Chengdu according to their characteristics and the number of people. This choice criterion ensures that the samples represent the specific population and the total geographical environment of Chengdu. The second stage is to allocate the sample size of each university proportionally using quota sampling. The proportion of sample size in each university is presented in Table 1. In the third stage, the researchers used purposive and convenience sampling to selectively select students with at least one semester of e-learning experience and issue questionnaires online through social networks to reach the target respondents' availability and willingness to respond when the questionnaire was distributed.

Table 1: Sample Units and Sample Size

University Name	Population Size	Proportional Sample Size
Sichuan University	6.6	193
University of Electronic Science and Technology of China	4.2	123
Chengdu University of Technology	3.8	111
Chengdu University of Information Technology	2.5	73
Total	**17.1**	**500**

Source: Constructed by author

4. Results and Discussion

4.1 Demographic Information

The survey obtained demographic information about gender, student status, duration of daily e-learning usage, major category, and preferred types of e-learning resources from the respondents. The questionnaire was distributed to 500 selected students from the four chosen institutions of higher education located in Chengdu. Among the respondents, 329 were males, accounting for 65.8 percent, and 171 were females, accounting for 34.2 percent. There are 400 students aged 18-22, accounting for 80.0 percent; 86 students aged 23-28, accounting for 17.2 percent; 14 students aged 29-35, accounting for 2.8 percent. There are 393 undergraduates, accounting for 78.6 percent, and 107 graduate students, accounting for 21.4 percent.

Eighty-nine people used e-learning for less than 1 hour a day, accounting for 17.8 percent; 215 people used 1 to 2 hours, accounting for 43.0 percent; 101 people used 2 to 4 hours, accounting for 20.2 percent, and 95 people used more than 4 hours, accounting for 19.0 percent. One person majored in educational psychology, accounting for 0.2 percent; 293 people majored in science and engineering, accounting for 58.6 percent; 2 people majored in literature, history, and philosophy, accounting for 0.4 percent; 60 people majored in economic management law, accounting for 12.0 percent, 16 people majored in agriculture, forestry, and medicine, accounting for 3.2 percent, 128 people majored in other, accounting for 25.6 percent. The results are shown in Table 2.

Table 2: Demographic Profile

Demographic and General Data (N=500)		Frequency	Percentage
Gender	Male	329	65.8%
	Female	171	34.2%
Age	18 to 22 years old	400	80.0%
	23 to 28 years old	86	17.2%
	29 to 35 years old	14	2.8%
Student status	Undergraduate	393	78.6%
	Graduate	107	21.4%
Duration of daily	Less than 1 hour	89	17.8%
	1-2 hours	215	43.0%

The Scholar: Human Sciences

Demographic and General Data (N=500)		Frequency	Percentage
e-learning usage	2-4 hours	101	20.2%
	More than 4 hours	95	19.0%
Major category	Educational Psychology	1	0.2%
	Science and engineering	293	58.6%
	Literature, History and Philosophy	2	0.4%
	Economic Management Law	60	12.0%
	Agriculture, forestry and medicine	16	3.2%
	Other	128	25.6%

4.2 Confirmatory Factor Analysis (CFA)

Confirmatory factor analysis (CFA) is a statistical method to validate measurement models. According to Anderson and Gerbing (1984), it is necessary to use confirmatory factor analysis to examine the measurement model prior to estimating the complete structural model. This study used CFA to check whether the proposed factor structure fits the observed data and verify the model's validity.

The model fit goodness-of-fit test is a statistical method used to assess how well a model fits the data. In this study, the model is tested by the fit goodness-of-fit index.

Factor loading refers to the coefficient of association between each observed variable and various factors. The factor loading for each item in this study was above 0.50, mostly above 0.70, with a range of 0.515 ~ 0.904.

CR (Composite Reliability) is an indicator for measuring the internal consistency of measurement tools (Chin, 1998; Hair et al., 2011; Rahman et al., 2013), AVE (Average Variance Extracted) is an indicator for measuring the reliability of measurement tools Kline (2011). In CFA, CR and AVE are important indicators used to evaluate the fit and reliability of measurement models. The CR values obtained in this study are all higher than 0.7. Composite or construct reliability values range from 0.752 ~ to 0.908.

AVE values are not only greater than 0.4 but also greater than 0.5, which reflects high convergence validity, with a range of 0.511 ~ 0.711.

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
Interactivity (Int)	Steuer (1992)	3	0.739	0.515-0.824	0.752	0.511
Perceived usefulness (PU)	Bhattacherjee (2001)	4	0.885	0.752-0.904	0.890	0.670
Confirmation (Conf)	Bhattacherjee (2001)	3	0.863	0.775-0.862	0.863	0.679
Cognitive Absorption (CA)	Mpinganjira (2019)	3	0.813	0.683-0.840	0.824	0.611
Information Quality (IQ)	Lee et al. (2007)	6	0.896	0.737-0.800	0.896	0.591
System Quality (SQ)	DeLone and McLean (2003)	4	0.879	0.776-0.823	0.879	0.645
Satisfaction (Satisf)	Bhattacherjee (2001)	4	0.907	0.825-0.868	0.908	0.711

The selected goodness of fit index included the Chi-square value (CMIN/pdf), Goodness of Fit Index (GFI), Adjusted Goodness of Fit Index (AGFI), Root Mean Square Error of Approximation (RMSEA), Normed Fit Index (NFI), Comparative Fit Index (CFI), and Tucker-Lewis Index (TLI). The above indices evaluated Seven latent variables, including interactivity, perceived usefulness, confirmation, cognitive absorption, information quality, system quality, and satisfaction, as depicted in Table 4. As can be seen from Table 3, the statistical values of the detection indicators of the model are CMIN/DF =2.423, GFI =0.903, AGFI =0.878, NFI=0.918, CFI =0.950, TLI =0.942, RMSEA =0.053. The values of the goodness-of-fit indexes of the original measurement model are all in line with the standard requirements and have presented a model 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)	734/303 or 2.423
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.903
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.878
NFI	≥ 0.80 (Wu & Wang, 2006)	0.918
CFI	≥ 0.80 (Bentler, 1990)	0.950
TLI	≥ 0.80 (Sharma et al., 2005)	0.942
RMSEA	< 0.08 (Pedroso et al., 2016)	0.053
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, NFI = normalized fit index, CFI = comparative fit index, TLI = Tucker Lewis index, and RMSEA = root mean square error of approximation

Discriminant validity can be achieved by comparing the average AVE variance between the two constructs (Bove et al., 2009). Discriminant validity emerges when the mean extracted variance exceeds the squared structural correlation (Glynn, 2009). In the study, the square root value of AVE for each factor is greater than the maximum correlation coefficient between that factor and other factors, ensuring good discriminant validity. The results are shown in Table 5.

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Table 5: Discriminant Validity

	INT	PU	CONF	CA	IQ	SQ	SAT
INT	**0.715**						
PU	0.467	**0.819**					
CONF	0.330	0.604	**0.824**				
CA	0.292	0.534	0.542	**0.782**			
IQ	0.338	0.601	0.590	0.597	**0.769**		
SQ	0.241	0.355	0.285	0.320	0.424	**0.803**	
SAT	0.335	0.646	0.581	0.623	0.730	0.468	**0.843**

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

4.3 Structural Equation Model (SEM)

Structural equation modeling (SEM) was used to estimate and test the causal relationship model between latent variables; that is, the structural model was estimated and tested to assess the fit of the model and to analyze the relationship between the factors and their joint influence on the outcomes to identify the factors that impact the perceived usefulness, cognitive adoption, and satisfaction of college students with cloud-based e-learning. The results before the adjustment of the statistical values of each indicator and the results after recalculation based on the revised structural model are shown in Table 6. After Adjustment, the statistical values were CMIN/DF = 3.925, GFI = 0.850, AGFI = 0.808, NFI= 0.870, CFI = 0.899, TLI = 0.880, and RMSEA = 0.077. The above statistical values indicate that the structural model fit is optimized and confirmed.

Table 6: Goodness of Fit for Structural Model

Fit Index	Acceptable Criteria	Statistical Values Before Adjustment	Statistical Values After Adjustment
CMIN/ DF	< 5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	4.629	3.925
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.815	0.850
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.779	0.808
NFI	≥ 0.80 (Wu & Wang, 2006)	0.836	0.870
CFI	≥ 0.80 (Bentler, 1990)	0.866	0.899
TLI	≥ 0.80 (Sharma et al., 2005)	0.851	0.880
RMSEA	< 0.08 (Pedroso et al., 2016)	0.085	0.077
Model Summary		**Unacceptable Model Fit**	**Acceptable Model Fit**

Remark: CMIN/DF = The ratio of the chi-square value to degree of freedom, GFI = goodness-of-fit index, AGFI = adjusted goodness-of-fit index, NFI = normalized fit index, CFI = comparative fit index, TLI = Tucker Lewis index, and RMSEA = root mean square error of approximation

4.4 Research Hypothesis Testing Result

Regression and standardized path coefficients were used to verify the reasonableness of the hypothesis in the structural model and to determine the degree of correlation between the dependent and independent variables. As shown in Table 7, six proposed hypotheses were supported. Perceived usefulness was significantly impacted by interactivity; cognitive absorption was significantly impacted by confirmation. Information quality strongly impacted satisfaction, perceived usefulness, cognitive absorption, and system quality. Perceived usefulness was significantly impacted by interactivity.

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-value	Result
H1: INT→PU	0.578	10.288*	Supported
H2: CONF→CA	0.540	8.527*	Supported
H3: INT→SAT	-0.040	-0.769	Not Supported
H4: PU→SAT	0.382	7.329*	Supported
H5: CONF→SAT	0.054	1.231	Not Supported
H6: CA→SAT	0.265	5.378*	Supported
H7: IQ→SAT	0.583	11.141*	Supported
H8: SQ→SAT	0.196	5.025*	Supported

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

The relationship between interactivity and perceived usefulness has a standardized path coefficient of 0.578 and a t-value of 10.288 in H1. This supports previous studies by Pituch and Lee (2006), Cheng (2012), and Cho et al. (2009). Vivid product interaction technology guides learners to regard e-learning systems as effective learning tools, allowing learners to perceive the system's usefulness through the system's interactive ability. Interactivity is a major determinant of PU in e-learning systems.

Confirmation significantly impacted Cognitive absorption, with a standardized path coefficient of 0.540 and a t-value of 8.527 in H2. The learner's cognitive absorption can be realigned by their confirmation experience so that the cognitive absorption of learners is positively impacted by their confirmation of the system expectation (Roca et al., 2006).

Information quality strongly impacted satisfaction, perceived usefulness, cognitive absorption, and system quality. The direct impact of Information quality on satisfaction is significant at a standardized path coefficient of

The Scholar: Human Sciences

0.583 and t-value at 11.141 in H7, which supported the study of Saghapour et al. (2018), Zhang and Watts (2008) that high-quality information will facilitate students' comprehending of curriculum content and lecture disputations, and sense encouraged from others, thus satisfaction with the quality information of the system. High-quality information from cloud-based e-learning systems can improve learners' satisfaction. The second strongest impact on the satisfaction of cloud-based e-learning is perceived usefulness with a standardized path coefficient of 0.382 and t-value at 7.329 in H4. The finding was consistent with Lee (2010), Chen et al. (2018), and Joo et al. (2018), who deem e-learning systems to be useful and believe that satisfaction with the system will be higher. The third strongest impact on the satisfaction of cloud-based e-learning is cognitive absorption, with a standardized path coefficient of 0.265 and a t-value of 5.378 in H6. This supports the view of Roca et al. (2006) and Leong (2011) that motivating learners' cognitive absorption levels through the e-learning system can actively lead them to a system of high satisfaction. The fourth strongest impact on the satisfaction of cloud-based e-learning is system quality with a standardized path coefficient of 0.196 and t-value at 5.025 in H8. The finding was consistent with previous studies by Almaiah and Alismaiel (2019) that a high-quality e-learning system serves assistance and venues for students and teachers, and system quality actively affects students' satisfaction (Almaiah & Alismaiel, 2019).

Satisfaction was not impacted by interactivity at a standardized path coefficient of -0.040 and t-value at -0.769. Hence H3 is not supported. Also, confirmation did not impact satisfaction at a standardized path coefficient of 0.054 and a t-value of 1.231. Hence, H5 is not supported.

5. Conclusion and Recommendation

5.1 Conclusion

This study aims to comprehensively analyze the determinant factors impacting college students' perceived usefulness, cognitive absorption, and satisfaction in cloud-based e-learning in Chengdu, China. The researchers formulated eight hypotheses to examine whether interactivity, confirmation, system quality, and information quality directly or indirectly impact the perceived usefulness, cognitive absorption, and satisfaction of cloud-based e-learning and whether perceived usefulness and cognitive absorption directly impact satisfaction. Centered on the ECM, D & M IS Success Model, and TAM, combined with three theoretical frameworks from previous studies, determined latent factors for a conceptual framework were identified. This research's target population is college students from four universities in Chengdu with at least one semester of e-learning experience. Questionnaires were distributed online to four university students with at least one semester of e-learning experience. This research used the stage-by-stage sampling procedure combined with non-probability sampling techniques to sample the research objects. CFA was used to measure and test the validity and reliability of the conceptual model through the collected data. The validity and reliability of the research conceptual model were measured through the results of convergent validity-composite reliability, Cronbach's alpha reliability, factor loading, average variance extracted analysis, and discriminant validity. SEM was utilized to validate the proposed research hypotheses and respond to the identified research questions by analyzing and discussing factors Impacting college students' perceived usefulness, cognitive absorption, and satisfaction in cloud-based e-learning.

Six of the eight hypotheses proposed were supported and proved to be able to achieve the research objectives. The findings of this study can be summarized into three main findings. First, interactivity is a strong predictor of perceived usefulness. The interactivity between learners and e-learning systems can energetically impact their PU towards the system (Chen, 2012; Cheng, 2012). In addition, students' satisfaction with cloud-based e-learning is indirectly impacted by interactivity, so interactivity is critical to improving perceived usefulness and indirectly impacts satisfaction.

Second, confirmation has a strong positive effect on cognitive absorption. Roca et al. (2006) found that learners' cognitive absorption can be modified by their experience confirmed using an e-learning system. Hence, learners' expected confirmation of the system actively impacts their cognitive absorption. In addition, students' satisfaction with cloud-based e-learning is indirectly impacted by confirmation, so confirmation is essential for improving cognitive absorption and indirectly impacts satisfaction.

Finally, information quality is the strongest predictor of satisfaction among the four factors that directly impact satisfaction, namely perceived usefulness, cognitive absorption, information quality, and system quality. Seddon and Kiew (1996) also concluded that there is a forceful/momentous correlation between user satisfaction and information quality by examining the D&M IS success model. Therefore, ensuring the quality of the information in the system is very important to improving satisfaction.

To sum up, the research goal has been achieved. Interactivity directly impacts the perceived usefulness of cloud-based e-learning for college students in Chengdu, Sichuan, China. Cognitive absorption is the direct impacting factor. Information quality is the direct impacting factor of satisfaction, followed by perceived usefulness, cognitive absorption, and system quality. Interactivity and confirmation are the indirect impacting factors of satisfaction.

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5.2 Recommendation

The research found that to improve students' perceived usefulness, cognitive absorption, and satisfaction with cloud-based e-learning, key factors, including interactivity (Int), validation (Conf), cognitive absorption (CA), perceived usefulness (PU), information quality (IQ), and system quality (SQ), need to be developed and promoted.

In this study, interactivity was a strong predictor of perceived usefulness. This means that if learners perceive that the system provides vivid interactive techniques that enable them to collect relevant information effectively and efficiently, learners will view the e-learning system as a useful tool. The positive correlation between interaction degree and perceived usefulness positively impacts system satisfaction. Confirmation is a strong predictor of cognitive absorption, meaning learners' cognitive absorption can be readjusted through their confirmation experience. Learners' confirmation of system expectations has a positive impact on learners' cognitive absorption. The positive correlation between recognition degree and cognitive absorption positively impacts system satisfaction. Information quality is the strongest predictor of satisfaction, so it is important to emphasize promoting information quality in the system. Perceived usefulness, cognitive absorption, and system quality were also strong predictors of satisfaction. According to the above results, curriculum developers, teachers, and senior managers of higher education institutions should consider system functions comprehensively when developing and utilizing cloud-based e-learning systems, starting from providing good interactivity mechanism, confirmation, perceived usefulness, cognitive absorption, information quality, and system quality. Among them, it should emphasize the interactivity of the system, the confirmation that can be provided to the user, and the information accuracy, accuracy, responsiveness, reliability, integrity, universality, that is, information quality. This also means that to improve students' perceived usefulness, cognitive absorption, and satisfaction in cloud-based e-learning, it is necessary first to make the system function better and of higher quality, which requires advanced and high-quality technical support. Before developing or optimizing the system, developers should be fully trained to improve their technical capabilities. Enable relevant operators to deeply understand the basic requirements, specific performance, and practical application of the software, establish a more reliable system with functions, and ensure external protection so as to help students effectively carry out cloud-based e-learning and improve their perceived usefulness, cognitive absorption and satisfaction of cloud-based e-learning. When the quality and function of cloud-based e-learning are guaranteed, cloud-based e-learning should be vigorously promoted to students, and the characteristics, main functions, and advantages of cloud-based e-learning should be promoted through campus media, social media, campus advertisements, and associations to improve students' understanding and enable them to gain deeper feelings during use. Thus helping to improve their perceived usefulness, cognitive absorption, and satisfaction with the cloud-based e-learning process.

In conclusion, this study explains in detail the factors impacting the perceived usefulness, cognitive absorption, and satisfaction of cloud-based e-learning for college students. It provides developers of cloud-based e-learning and senior administrators of colleges and universities with the ability to identify variables that impact the perceived usefulness, cognitive absorption, and satisfaction of cloud-based e-learning for college students in order to optimize the cloud-based e-learning system better; it gives full play to its advantages to provide students with better cloud-based e-learning services and guarantees and apply it to projects and investments.

5.3 Limitation and Further Study

This study also has its limitations.

Firstly, the research institutions were single. This study only concentrates on domestic higher education institutions, and the sample data only comes from four selected universities in Chengdu. Later research can expand to more training and learning institutions and basic education research, increase the survey scope and quantity of samples, and make the research results more universal.

Secondly, the subjects were single, and the object of this research is only centered solely on university students. In future explorations, teachers, trainers, etc., could be incorporated to obtain a broader perspective of the demand for cloud-based e-learning and their perceptions of perceived usefulness, cognitive absorption, and satisfaction.

Thirdly, this present study focuses only on cloud-based e-learning and its application in education. Further exploration can be carried out on different sorts of e-learning systems or the application of e-learning for diverse objectives.

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