pISSN: 1906 - 6406 The Scholar: Human Sciences
eISSN: 2586 - 9388 The Scholar: Human Sciences
https://assumptionjournal.au.edu/index.php/Scholar

Exploring the Drivers of Undergraduates' Perceived Usefulness and Intention to Adopt Cloud Computing: A Study in Chengdu, China

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Received: August 29, 2024. Revised: September 16, 2024. Accepted: Frebuary 18, 2025.

Abstract

Purpose: This paper investigates the elements that affect the perceived usefulness and intention to use cloud computing among undergraduates in Chengdu, China. Seven latent variables were specifically chosen, which were perceived ease of use, subjective norms, perceived usefulness, attitude, perceived cost of usage, perceived security, and intention to use. **Research Design, Data, and Methodology:** The researcher employed quantitative research methodologies and delivered 500 questionnaires to undergraduates at the target universities who were enrolled in four key majors. This survey made use of the multistage sampling approach. The associations between the variables under investigation were ascertained using the structural equation model (SEM) and confirmatory factor analysis (CFA). The examination of the research data validated all the conjectures, revealing that the technology's perceived usefulness was the key motivator for university students to interact with cloud computing. **Results:** The results indicated important references for curriculum design and promotion strategies in cloud computing education in universities, as well as empirical evidence for education administrators and policymakers to formulate more effective educational technology policies, encouraging the incorporation and assimilation of cloud computing technologies within academic environments, thereby enhancing its accessibility and utilization. **Conclusions:** The findings revealed that perceived usefulness exerted the greatest pronounced influence on the dependent variable, affecting the decision to employ cloud computing.

Keywords: Cloud Computing, Subjective Norms, Perceived Usefulness, Attitude, Intention to Use

JEL Classification Code: E44, F31, F37, G15

1. Introduction

Cloud computing was an innovative model that enabled users to access adaptable computer resources quickly and easily from anywhere via a network. These assets, which could be swiftly deployed and delivered with little administrative overhead or engagement with service providers, included systems, servers, storage, software, and services (Mell & Grance, 2011). Rayport and Heyward (2009) stated that this new deployment allowed people to work together, access, share, and save data online. Cloud computing, with its unparalleled flexibility, scalability, and cost reductions, has revolutionized the operations of businesses.

Emerging technologies, including data analytics and AI, along with rapid digital transformation, are propelling the exponential growth of the worldwide cloud computing market. Driven by the Chinese government's policy support and the digital transformation of enterprises, cloud computing is developing rapidly in the Chinese market, playing an important role in supporting the real economy, promoting changes in social productivity, meeting the needs of spiritual civilization, and other elements of the country's

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comprehensive strength. In higher education, cloud computing has become a cornerstone for enhancing teaching, learning, and administrative processes. In order to address the growing need for digital learning solutions, spur educational innovation, and optimize their IT infrastructure, more and more colleges are embracing cloud computing technology.

Based on the context above, this study combines the Theory of Planned Behavior (TPB) and the Technology Acceptance Model (TAM) to investigate significant determinants impacting undergraduates' intention to use cloud computing in Chengdu, China, and their perceptions of its utility. The study's conclusions will greatly assist academic institutions, policymakers, and technology providers, thereby facilitating the integration and effective deployment of cloud computing in academic environments.

2. Literature Review

2.1 Perceived Ease of Use

The concept of "perceived ease of use" was about the expected amount of work required by a prospective user to operate a specific technology or system, as noted by Revels et al. (2010). Safeena et al. (2011) echoed this by defining it as the extent of perceived exertion users believed was necessary to engage with a system or service. Chen (2015) research, this perception was pinpointed as pivotal in boosting the perceived value of innovative technology services. Furthermore, Changchit and Chuchuen (2016) study corroborated that consumers' inclination to embrace cloud computing was largely influenced by their favorable views on its ease of use. Moreover, Huang (2017) revealed that individuals were more inclined to consider a technology advantageous and intend to adopt it when they perceived it as simple.

H1: Perceived ease of use has a significant effect on perceived usefulness.

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

2.2 Perceived Usefulness

Perceived usefulness represented how much users believed that using information technology (IT) would bring significant value to them (Ajzen, 1991). Q. Chen et al. (2007) identified that the belief among users that a system could enhance their work efficiency was termed "perceived usefulness." This belief positively motivated users to adopt the system. Whether a person was willing to adopt information technology largely depended on their perception of its utility (Suki & Suki, 2011). Perceived usefulness significantly influenced cloud computing intentions within the higher education environment (Militaru et al., 2016). Users of mobile cloud storage services reported significant productivity increases, and people's inclination to utilize personal cloud storage services was positively influenced by their view of its usefulness (Park & Kim, 2014).

H3: Perceived usefulness has a significant effect on intention to use.

2.3 Attitude

Fishbein and Ajzen (1975) pointed out, attitude refers to someone's sentiments about engaging in a particular behavior, whether that emotion is favorable or unfavorable. Chocarro et al. (2021) pointed out that the idea of attitude included a variety of aspects, such as emotive, cognitive, and behavioral elements that collectively affected how people evaluated their capacity to use a specific system (Dajani et al., 2022). Predicting consumer behavior toward products or services requires understanding their sentiments (Chanda et al., 2023). Behrend et al. (2011) believed that users' attitudes toward a behavior indicated how suitable or unsuitable they found the behavior, reflecting their perceived personal intention to use it. Asadi et al. (2017) determined that a favorable disposition toward embracing cloud computing services and applications profoundly affected the willingness to use them.

H4: Attitude has a significant effect on intention to use.

2.4 Perceived Cost of Usage

Changchit and Chuchuen (2016) described perceived usage costs as encompassing the expenses of using information and communication technologies (ICT), including monetary, time, effort, and opportunity costs. This concept referred to the costs users believed they needed to incur to use a cloud computing service, reflecting their perception of the expenses associated with utilizing a specific technology, product, or service (Tripathi, 2017). Wang et al. (2023) noted that high perceived costs could diminish the intention to use ICT. High acquisition, education, and time expenses are major disincentives for IT technology users. According to Changchit (2014), students' adoption of cloud computing was shown to be highly impacted by their perception of its cost. Students tended to adopt cloud computing when they saw it as a cost-effective option. Similarly, individuals were more inclined to embrace new technology when they believed the associated costs were reasonable. This is because, regardless of the advantages of the technology, it becomes unfeasible if the costs exceed the benefits (Rababah et al., 2017).

H5: Perceived cost of usage has a significant effect on intention to use.

2.5 Perceived Security

Chellappa and Pavlou (2002) state that perceived security protects against risks, injuries, losses, and criminal activities. Changchit and Chuchuen (2016) highlighted an individual's perception of security as the probability that personal information would remain confidential, unaltered, and secure from unauthorized access or tampering during storage or transmission. When students thought cloud computing was safe, they tended to prefer it. Ali et al. (2020) emphasized that security perception was significant in molding individuals' readiness to use cloud computing. Nikkhah and Sabherwal (2022) revealed that perceived security impacted privacy decision-making, with a higher perception of security leading to a greater willingness to share personal information. Additionally, Changchit (2014) observed that individuals were more inclined to explore and adopt cloud technology when they were confident about the security of their data stored remotely.

H6: Perceived security has a significant effect on intention to use.

2.6. Subjective Norms

Subjective norms were people's judgments about important others' attitudes and ideas about whether they should participate in a specific conduct (Fishbein & Ajzen, 1975). These norms concerned the degree to which a user felt that powerful people, such as those with high status, thought they should utilize the new IT regarding technology adoption (Venkatesh & Davis, 2000). Research by Singh and Kaur (2021) showed that subjective norms were a reliable predictor of individuals' behavioral intentions, illustrating the significant impact one person's beliefs could have on another's decision-making regarding technology use (Choe et al., 2021). Vafaei-Zadeh et al. (2019) positively correlated subjective norms and intention to use, highlighting the favorable impact of media, social networks, friends, and family on users' readiness to embrace software. Furthermore, Tavakoli et al. (2023) verified that favorable subjective norms significantly influenced the inclination toward cloud computing services.

H7: Subjective norms have a significant effect on intention to use.

2.7 Intention to Use

Intention to use refers to an individual's cognitive thoughts and perceptions regarding their willingness to embrace a certain technology (Hasan et al., 2020). Within cloud computing, the focus was primarily on consumers' inclination to utilize various services and applications provided by cloud computing platforms (Chen, 2015). The actual conduct of an individual was determined by their behavioral intention to engage in a specific activity (Fishbein & Ajzen, 1975). Individual readiness to embrace new technological advancements was demonstrated by their propensity to engage with them (Venkatesh & Davis, 2000). A predictor of information technology adoption behavior was the intention to use, which was influenced by motivational factors driving the behavior. The more logical and beneficial the behavior seemed, the more likely it was to be adopted (Başaran & Hussein, 2023).

3. Research Methods and Materials

3.1 Research Framework

We examined methodologies from prior scholarly work to construct the foundational theory for this investigation. This study drew on TPB, TAM, and three other major theoretical frameworks, according to Chen (2015), identified a relationship between perceived usefulness and perceived ease of use. Changchit and Chuchuen (2016) empirically established the correlation among perceived usefulness, perceived ease of use, perceived cost of usage, perceived security, and intention to use. The linkages among subjective norms, attitudes, and intention to use were corroborated by Asadi et al. (2019). We have developed a conceptual framework incorporating these theoretical constructs, depicted in Figure 1.

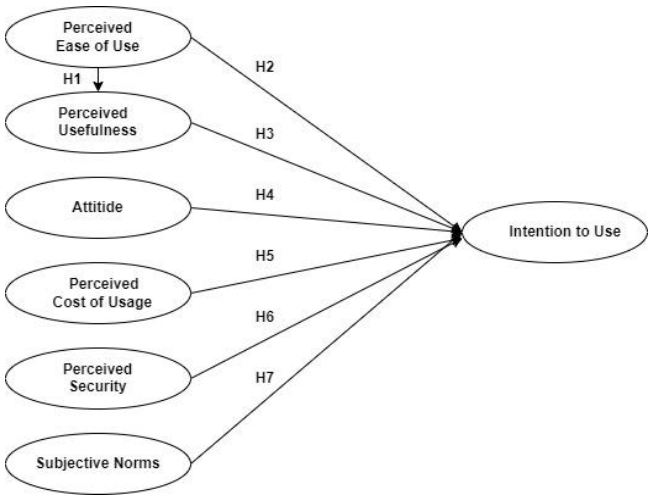

Figure 1: Research Conceptual Framework

H1: Perceived ease of use has a significant effect on perceived usefulness.
H2: Perceived ease of use has a significant effect on intention to use.
H3: Perceived usefulness has a significant effect on intention to use.
H4: Attitude has a significant effect on intention to use.
H5: Perceived cost of usage has a significant effect on intention to use.
H6: Perceived security has a significant effect on intention to use.
H7: Subjective norms have a significant effect on intention to use.

3.2 Research Methodology

The researchers used probability sampling to survey undergraduates from four key majors at Geely University of China. These majors include Computer Science and Technology, Virtual Reality Technology, Data Science and Big Data Technology, and Network Engineering. Through a comprehensive review and analysis of the data gathered the researchers sought to determine the key variables that significantly influence the decision to utilize cloud computing. The questionnaire comprised three sections: questions for screening, questions for demographics, and questions for variable measures.

First, the screening questions, an essential part of the questionnaire, were used to determine whether the respondents met specific criteria or were eligible to finish the survey (Young, 2015). Subsequently, the researchers created a series of demographic inquiries to gather fundamental data from undergraduate students, including gender, grade, major, and kind of resource utilization. Lastly, the researchers used a 5-level Likert scale to rate the questions' responses. According to Joshi et al. (2015), every response on the Likert scale was given a number value representing the respondent's positive or negative attitude: A score of five signified strong agreement, whereas a score of one indicated severe disagreement.

To evaluate the accuracy of the research tool created specifically for this project, the researchers invited three experts with doctoral education backgrounds in cloud computing to conduct a content validity test for item-objective congruence. To confirm the tool's reliability, 50 students also took part in a pilot study. 500 undergraduates from the target university received paper questionnaires after the questionnaire's reliability and accuracy were established. Jamovi was used to evaluate the study's statistical data. Furthermore, factor loadings, statistical significance (t-values), composite reliability (CR), average variance extracted (AVE), and discriminant validity were examined by the researchers using confirmatory factor analysis (CFA). The study employed structural equation modeling (SEM) to evaluate the immediate and mediated linkages between these unobserved elements.

3.3 Population and Sample Size

The survey focused on undergraduates majoring in four key fields at Geely University of China. From these majors, 1235 students with at least a year's experience with cloud computing were chosen. Professional statistical calculators were used to establish the minimal sample size of 425 participants, as the study's framework comprised seven latent variables and twenty-five observable variables. Using a quota sampling technique, A conclusive group of 500 participants was chosen from the designated four fields, ensuring the data's credibility.

3.4 Sampling Technique

The researcher employed a multi-stage sampling approach consisting of two primary components. First, they employed judgment sampling to determine which 1235 students from the four target majors had at least a year's cloud computing experience. After that, 500 respondents were selected from these four majors through quota sampling to form the final sample.

Table 1: Sample Units and Sample Size

Target Majors	Grade	Population Size Total	Proportional Sample Size Total
Computer Science and Technology	Freshman	92	37
	Sophomore	150	61
	Junior	157	64
	Senior	142	57
Network Engineering	Freshman	65	26
	Sophomore	93	38
	Junior	116	47
	Senior	106	43
Data Science and Big Data Technology	Freshman	43	18
	Sophomore	58	24
	Junior	62	25
	Senior	50	20
Virtual Reality Technology	Freshman	20	8
	Sophomore	26	10
	Junior	30	12
	Senior	25	10
Total		**1235**	**500**

Source: Constructed by author

4. Results and Discussion

4.1 Demographic Information

Table 2 presents an extensive summary of the demographic data for the 500 participants. Of these, 61.20% were male and 38.80% were female. The following was the breakdown of majors: 43.80% in Computer Science and Technology, 30.80% in Network Engineering, 17.20% in Data Science and Big Data Technology, and 8.20% in Virtual Reality Technology. Regarding academic standing, 17.6% of participants were first-year students, 26.8% second-years, 29.6% third-years, and 26% final-years. Regarding the engagement with cloud computing services, 22.40% of the students used cloud computing network resources, 16.20% used cloud computing resources, 25.00% used cloud computing storage resources, and 36.40% used cloud computing application software resources.

Table 2: Demographic Profile

Demographic and General Data (N=500)		Frequency	Percentage
Gender	Male	306	61.20%
	Female	194	38.80%
Major	Computer Science and	219	43.80%
	Network Engineering	154	30.80%
	Data Science and Big	86	17.20%
	Virtual Reality Techno	41	8.20%
Grade	Freshman	88	17.60%
	Sophomore	134	26.80%
	Junior	148	29.60%
	Senior	130	26.00%
Type of cloud computing used	Network	112	22.40%
	Computing	81	16.20%
	Storage	125	25.00%
	Application Software	182	36.40%

4.2 Confirmatory Factor Analysis (CFA)

Confirmatory Factor Analysis (CFA) is used to quantitatively verify the quantity and arrangement of factors, ensuring consistency between the measured variables and the theoretical constructs as posited in the hypothesis (Malhotra et al., 2004).

Table 3 illustrates that the six underlying constructs had Cronbach's alpha coefficients exceeding 0.80**,** with one above 0.90. The average variance extracted (AVE) (exceeding 0.50)**,** composite reliability (CR) (exceeding 0.70)**,** and total factor loadings (exceeding 0.50) met the required criteria. The square root of the average variance extracted (AVE) for each construct is higher than the inter-correlations among any pair of latent variables.

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

Variables	Source of Questionnaire (Measurement Indicator)	No. of Item	Cronbach's Alpha	Factors Loading	CR	AVE
Perceived Ease of Use (PEOU)	Changchit and Chuchuen (2016)	4	0.900	0.806-0.863	0.901	0.694
Perceived Usefulness (PU)	Changchit and Chuchuen (2016)	4	0.873	0.761-0.834	0.874	0.634
Attitude (ATT)	Asadi et al. (2019)	3	0.841	0.771-0.826	0.841	0.639
Perceived Cost of Usage (PCOU)	Changchit and Chuchuen (2016)	4	0.895	0.816-0.834	0.896	0.682
Perceived Security (PS)	Changchit and Chuchuen (2016)	4	0.896	0.795-0.848	0.897	0.685
Subjective Norms (SN)	Chanda et al. (2023)	3	0.857	0.811-0.823	0.857	0.666
Intention to Use (INT)	Chanda et al. (2023)	3	0.825	0.769-0.793	0.825	0.611

Table 4 presents the criteria for various model fit indices, including the Tucker-Lewis index (TLI), comparative fit index (CFI), normed fit index (NFI), goodness-of-fit index (GFI), adjusted goodness-of-fit index (AGFI), and chi-square value to the degree of freedom ratio (CMIN/DF). These indices collectively evaluated the model's fit characteristics. The results indicated that all goodness-of-fit metrics evaluated in this study using confirmatory factor analysis were satisfactory.

Table 4: Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	< 5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	1.204
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.954
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.941
NFI	≥ 0.80 (Wu & Wang, 2006)	0.957
CFI	≥ 0.80 (Bentler, 1990)	0.992
TLI	≥ 0.80 (Sharma et al., 2005)	0.991
RMSEA	< 0.08 (Pedroso et al., 2016)	0.020
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

According to the discriminant validity data in Table 5, all these correlations are below the 0.80 mark. Therefore, these quantitative measurements were used to establish discriminant validity.

Table 5: Discriminant Validity

	PEOU	PU	ATT	PCOU	PS	SN	INT
PEOU	**0.833**						
PU	0.276	**0.796**					
ATT	0.278	0.15	**0.799**				
PCOU	0.274	0.255	0.197	**0.826**			
PS	0.246	0.275	0.237	0.234	**0.828**		
SN	0.249	0.25	0.216	0.265	0.273	**0.816**	
INT	0.333	0.371	0.274	0.324	0.314	0.311	**0.782**

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

4.3 Structural Equation Model (SEM)

Consistent with the goals of this study, the structural equation model (SEM) was confirmed via confirmatory factor analysis (CFA). SEM is a statistical technique employed to assess a collection of linear relationships designed to verify the soundness of the theoretical causal model. Additionally, SEM considered measurement errors in the coefficients and scrutinized the causal linkages between variables within a specific matrix (Byrne, 2016). Table 6 demonstrates that following AMOS adjustments, The metrics, including CMIN/DF, GFI, AGFI, CFI, NFI, TLI, and RMSEA, all meet the satisfactory criteria. As such, the appropriateness of the SEM was validated.

Table 6: Goodness of Fit for Structural Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/ DF	< 5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	2.162
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.904
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.883
NFI	≥ 0.80 (Wu & Wang, 2006)	0.919
CFI	≥ 0.80 (Bentler, 1990)	0.954
TLI	≥ 0.80 (Sharma et al., 2005)	0.949
RMSEA	< 0.08 (Pedroso et al., 2016)	0.048
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

4.4 Research Hypothesis Testing Result

As indicated in Table 7, the perceived usefulness exerted the most substantial direct effect on the intention to use, reflected by a standardized path coefficient (β) of 0.264, supported by a t-value of 4.910 ($p < 0.001$). The influence of the perceived cost of usage on the intention to use was the second most impactful, with a β value of 0.185, backed by a t-value of 3.757 ($p < 0.001$). The intention to utilize was notably influenced by the perceived ease of use, as indicated by a β value of 0.170, with a corresponding t-value of 3.281 ($p < 0.01$). Furthermore, the influence of subjective norms and perceived security was also evident, with respective β values of 0.164 and 0.166, accompanied by t-values of 2.277 ($p < 0.01$) and 3.377 ($p < 0.001$). Intention to use was also influenced by attitude, with a β value of 0.153 and a t value of 3.030 ($p < 0.01$). Within the TAM theoretical structure, perceived usefulness had the largest effect, especially in the interaction with perceived ease of use, characterized by a β value of 0.311 and a t value of 6.224 ($p < 0.001$).

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-value	Result
H1: PEOU→PU	0.311	6.224***	Supported
H2: PEOU→INT	0.170	3.281**	Supported
H3: PU→INT	0.264	4.910***	Supported
H4: ATT→INT	0.153	3.030**	Supported
H5: PCOU→INT	0.185	3.757***	Supported
H6: PS→INT	0.166	3.377***	Supported
H7: SN→INT	0.164	2.277**	Supported

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

The findings from Table 7 prompted the researchers to recommend the following courses of action:

H1 indicated that perceived ease of use significantly influenced perceived usefulness, as reflected in a standardized path coefficient value of 0.311. Li and Varghese (2023) found that users were more likely to embrace technology when they found it easier to use. The study indicated that consumers were more inclined to adopt cloud computing if they found it intuitive and believed it would enhance their productivity or improve their learning experience. On the other hand, people who found cloud computing challenging to use were more likely to think that the technology would not improve their learning or productivity, which made them less likely to accept it.

The standardized path coefficient value of 0.170 for H2 emphasized that the perceived ease of use significantly influenced users' intention to use. Changchit and Chuchuen (2016) corroborated that when consumers perceive cloud technology as easy to use, they are more likely to adopt it for various tasks and applications. This suggested that individuals were more inclined to integrate cloud computing into their daily routines, work responsibilities, and educational endeavors when they perceived it as user-friendly.

Additionally, the empirical data supporting H3 demonstrated that perceived usefulness served as a pivotal

link in the association between technology adoption intentions and the characteristics perceived by users, exhibiting the highest standardized path coefficient of 0.264 among all attributes affecting the intention to use. According to Suki & Suki (2011), users' willingness to adopt information technology depended largely on their perceptions of its usefulness. That is, when users perceived cloud computing as useful, they were more inclined to seamlessly integrate it into their work, study, and living environments and explore innovative applications of cloud computing technology.

Moreover, H4 has demonstrated that a standardized path coefficient value of 0.153 supports the involvement of attitude as a direct influence on the intention to use. Chanda et al. (2023) emphasized that customers' intentions to use personal cloud storage services were positively impacted by their sentiments regarding these services. This implied that students were more likely to get interested in using cloud computing if they had a positive mindset.

H5's findings indicated that the intention to use was notably swayed by the perceived cost of usage, highlighted by a standardized path coefficient of 0.185. According to Changchit (2014), students' adoption of cloud computing was shown to be highly impacted by their perception of its cost. This indicated that when cloud computing was seen as having a low cost, students were more likely to use it.

According to the statistical analysis results for H6, a standardized path coefficient of 0.166 highlighted the significant influence that perceived security had on the intention to use. As stated by Rababah et al. (2017), students' inclination to adopt cloud computing was positively impacted by their perception of security. In essence, students demonstrated greater willingness to embrace and engage with cloud technology when they perceived it to be secure.

Finally, H7 confirmed that the intention to use the technology significantly correlated with subjective norms, supported by a standardized path coefficient of 0.164. Tavakoli et al. (2023) found subjective norms favorably associated with the willingness to utilize technology. Undergraduates were likelier to try and adopt cloud computing technology if they thought their peers, family, instructors, and close friends had favorable attitudes towards it and considered it a popular and accepted activity.

5. Conclusion and Recommendation

5.1 Conclusion

The findings revealed that perceived usefulness exerted the greatest pronounced influence on the dependent variable, affecting the decision to employ cloud computing. This implied that students' propensity to embrace cloud computing depended on how much they thought it might improve their learning and productivity. Next, the perceived cost of usage ranked second in influencing intention to use, indicating that students paid attention to the cost associated with cloud computing when deciding whether to adopt it. Perceived ease of use ranked third, reflecting how undergraduates' perceptions of how easy it was to use cloud computing directly affected their intention to use it. Perceived security ranked fourth, suggesting that students' perceptions of cloud computing's security had a similar impact on their intent to adopt it. Subjective norms ranked fifth, indicating that undergraduates' intention to use cloud computing was directly impacted by how well-received and accepted it was in their social circles. Attitude came in sixth place, highlighting how students' attitudes toward cloud computing influenced their intention to use it. Furthermore, consistent with the TAM hypothesis, the findings of this quantitative survey indicated that the perceived ease of use was the primary determinant impacting the perceived usefulness.

5.2 Recommendation

The Geely University of China study examined the underlying variables influencing undergraduates in four key majors' perceived usefulness and intention to use cloud computing. The research outcomes have led the investigators to recommend focusing on the relationships among perceived ease of use, perceived usefulness, attitudes, perceived cost of usage, perceived security, subjective norms, and the intention to use, as indicated by the quantitative analysis results. The subsequent suggestions are offered to provide more rational or sophisticated methods to increase students' inclination to utilize cloud computing and encourage the widespread use and advancement of cloud computing technology in the educational setting.

When considering the perceived ease of use, it is recommended to focus on enhancing the accessibility and simplicity of cloud computing solutions. This can be achieved by offering an intuitive user interface, streamlining the operational procedures, furnishing comprehensive guides and support materials, and organizing frequent training sessions to facilitate easy initiation and lower the entry hurdles for engaging with cloud computing.

For the perceived usefulness, publicity and promotion of the practical application effects of cloud computing should be strengthened. Case presentations, simulations of actual application scenarios, and projects and internships in which students are involved can be used to demonstrate the specific

advantages of cloud computing in improving work efficiency and optimizing the learning experience so that students can feel the convenience and benefits of cloud computing.

Regarding attitude, educational institutions should actively create an atmosphere of positive attitude towards cloud computing. Activities such as inviting industry experts to give lectures, organizing related technical competitions, and conducting seminars and forums on cloud computing technology can enhance undergraduates' interest in and recognition of cloud computing technology, thereby making them more likely to use it.

For the perceived cost of usage, the cost burden for undergraduates using cloud computing should be reduced as much as possible. Consideration can be given to providing free cloud computing resources and services, cooperating with commercial companies to provide preferential policies for students, and setting up special funds to support cloud computing technology to reduce economic pressure and increase motivation for use.

In terms of perceived security, security measures should be reinforced to raise the perceived level of security to protect student data and privacy. Regular security training, the adoption of stringent data protection and privacy rules, the deployment of cutting-edge encryption technologies, and other security measures can all help increase students' confidence in the security of cloud computing and enhance their inclination to utilize it.

Finally, regarding subjective norms, it is important to reinforce cloud computing's acceptance and acknowledgment in social settings. Universities can vigorously advocate for the implementation and widespread acceptance of cloud computing solutions, foster favorable perceptions around it, and enlighten students' social circles, including friends, relatives, and academic mentors, about the benefits and significance of cloud computing. When taken as a whole, these programs help undergraduates adopt cloud computing.

5.3 Limitation and Further Study

The research was confined to a specific segment of undergraduates at Geely University in China, focusing on four academic majors, with the theoretical model limited to seven potential variables. We have three options for further investigation: First, we can broaden the study's purview to include students from various Chinese universities, encompassing a range of geographic locations, types, and majors, to produce more thorough and representative results. Second, more technological acceptance theories, including TRA and UTAUT, can be added to provide a more thorough and multifaceted study framework. Finally, platform data can be mined to track and evaluate how students use and perform academically on cloud computing platforms, explore the elements determining perceived usefulness and intention to use cloud computing among undergraduates and provide optimization suggestions and decision support for educational institutions and technology developers.

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