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Influential Factors Shaping the Behavioral Intention of Undergraduate Students towards Livestream Shopping in Chengdu, China

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Abstract

Purpose: This study intends to investigate the factors influencing the choice of live shopping among students in Chengdu. The study explores the relationship between seven variables: perceived ease of use, perceived usefulness, perceived enjoyment, attitude, service quality, social influence, and behavioral intention. **Research design, data, and methodology:** The researcher used the quantitative method (n=500) to distribute questionnaires to undergraduate students in three designated universities in Chengdu. Considering the principle of similarity in geographical location and representativeness at the school level, the judgmental sampling was to select three universities. Quota sampling fixes the number, and convenience sampling helps with the data collection and distribution of surveys in multiple ways. The Structural Equation Model (SEM) and Confirmatory Factor Analysis (CFA) were used for the data analysis, and they included model fit, reliability, and validity of the constructs. **Results:** The results explicated that perceived ease of use, usefulness, and enjoyment significantly impact attitude. Moreover, attitude, service quality, and social influence significantly affect behavioral intention. **Conclusions:** All hypotheses were completely proven to fulfill research objectives. Hence, there is a need to continuously develop new technologies and improve the quality and level of service to meet consumers' different needs and tastes.

Keywords : Livestreaming Shopping, Behavioral Intention, Perceived Enjoyment, Attitude, Social Influence

JEL Classification Code: E44, F31, F37, G15

1. Introduction

With 62% of Internet users purchasing a product online at least once in the first half of 2004, the Internet is currently the shopping channel with the quickest rate of growth (Aqute Research, 2004). Livestream purchasing is a new type of social commerce that is included on Facebook, Taobao, and other well-known social networking sites. Sellers can connect with viewers and exhibit products in real-time through livestream shopping. By publishing bullet screens, viewers can consult, ask questions, offer recommendations, and express their opinions and remarks.

Acknowledging that internet shopping platforms have significantly altered consumers' buying habits is unavoidable. Big data will enable precise product categorization and delivery to prospective clients, facilitating simple decision-making. Taobao Live, one of mainland China's most widely used live-streaming platforms, has had a 32% consumer conversion rate lately. Users add 320,000 products to their shopping carts for every million views. Since 2001, live streaming has quickly expanded due to its ease of use for multimedia interaction and its emergence as a novel social media platform (Hilvert-Bruce et al., 2018). China's three most widely used live broadcasting sites are Jing Dong, TikTok, and Tao Bao. Our research focuses on livestream buying to use questionnaires to examine the variables that affect livestream shoppers' behavioral intentions.

The big thing in the future will be livestream buying. Since the epidemic first surfaced in 2020, several companies and merchants have drawn customers through live broadcasts, particularly today's youth (Guo et al., 2021). However, live broadcasts create social media profiles, which

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they use to market and sell products. Naturally, China's internet shopping malls are the primary source of sales channels.

Live streaming has become increasingly popular worldwide. The global live-streaming industry is predicted to grow from USD 30.29 billion to USD 70.05 billion between 2016 and 2021 (Research & Markets, 2016). Consider TikTok, the previous amazing app for short videos, as an example of a live broadcast application. Anybody can watch various legal and compliant live broadcasts as they like, and anyone can broadcast any content at any time and from any location.

The anchor functions as the "shopping guide" in the real store while people shop live. Customers' confidence in the product is substantially increased by their thorough explanations and prompt responses to their questions. Then, viewers may talk and engage with the anchor while watching the live show and place orders whenever they like. The anchor can promptly address the queries and demands of the viewers and their recommendations. The anchor engages in constant conversation and interaction with the audience. Customers are thus sufficiently trusting due to the live broadcast's authenticity and visualization (Hu & Chaudhry, 2020).

Thus, our doctoral dissertation aims to investigate behavioral intention among graduate and undergraduate students at three Chengdu institutions. We investigate how the live broadcast platform endures in the highly competitive market. How can I grab students' interest and add anything worthwhile? How does it impact students' desire to engage in livestream purchasing going forward?

2. Literature Review

2.1 Perceived Ease of Use

Davis (1989) defined perceived ease of use as "a measure of the effort a user can save by using a specific product." Put differently, perceived ease of use can also be described as the degree to which prospective users anticipate a new technology to be convenient.

According to Davis (1988), the term "ease of use" refers to a person's confidence level when utilizing a particular product—that is, when specific products do not require much work on the user's part. We have established that PEOU encourages the beneficial usage of specific items and is closely linked to PU (Davis et al., 1989). Users will find a product more valuable and be able to accomplish more activities at once with greater efficiency if it is easy to use.

Perceived usefulness (PU) and perceived ease of use (PEOU) are the two most important variables in the Technology Acceptance Model (TAM), which was developed by Davis et al. (1989) based on rational action theory. These variables primarily drive the explanation of how the two interact and act together on the third factor in the field of information technology (Davis et al., 1989). Venkatesh and Davis (2000) assert that a technology's utility increases with its ease of use. Put another way; people are more likely to recognize and accept the benefits of a technology or service if they find it straightforward to use. As a result, PEOU has excellent PU prediction. Given this perspective, this study suggests the following hypotheses:

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

H2: Perceived ease of use has a significant impact on perceived enjoyment.

H4: Perceived ease of use has a significant impact on attitude.

2.2 Perceived Usefulness

The definition of perceived usefulness is the extent to which an individual believes that his or her performance has improved after using a specific system" (Davis, 1989). This indicates that users understand how beneficial the product is for completing their jobs, including fewer working hours and increased accuracy and efficiency (Lee et al., 2012). To sum up, perceived usefulness gauges a person's confidence in utilizing a system or technology to boost productivity at work. Perceived usefulness is defined as the ability to use a system to make work easier and more efficient, contributing to increased production and, ultimately, leading to a promotion or pay increase, extra bonuses, or other awards, etc. Perceived utility and perceived ease of use are major factors in determining whether people utilize e-government services, according to research on the TAM model used in e-government (Dimitrova & Chen, 2006).

According to a study by Wong and Zhou (2015), perceived enjoyment impacts the intention to use a mobile learning system. To forecast users' acceptance and adoption rates of new technologies, Zhou and Ee (2012) and Yang and Wu (2012) integrated PE into the UTAUT model. They discovered that PE's attitude toward utilizing a particular system had a beneficial influence under such a framework.

According to early research, positive universalization (PU) benefits attitude (Lin & Lu, 2011). Attitude is a person's assessment of a certain activity, which can be neutral, positive, or negative. Perceived utility (PU) and perceived ease of use (PEOU) jointly influence people's attitudes about using technology, which in turn influences behavioral intentions, as the basic TAM model makes evident (Kim & Forsythe, 2008; Lee, 2006; Pantano & Migliarese, 2014). Previous research indicates that compatibility, PU, PE, PEOU, and compatibility—all major TAM variables—impact attitudes. As a result, a hypothesis is assumed as the

following:
H3: Perceived usefulness has a significant impact on attitude.

2.3 Perceived Enjoyment

According to Davis et al. (1992), perceived enjoyment (PE) refers to how much a person enjoys using a computer during the actual process of using it, minus any potential expected outcomes. The degree to which one perceives pleasure is known as perceived enjoyment, and it does not consider the outcome of employing a certain system.

The level of pleasure a user feels when using a computer, independent of the outcome, is known as perceived enjoyment (PE) (Davis et al., 1992). Studies demonstrate that PE is a significant factor in users' behavioral intention to select new technologies, particularly those hedonic systems or technologies. We discovered that a significant body of research has validated the relationship between PE and PEOU and that PEOU directly influences PE.

Simultaneously, we validated the impact of an additional direction (PEOU > PE) in the TAM model investigation. Deci (1975) or Davis (1989) and Davis et al. (1992) technology acceptance motivation model frequently include this correlation. According to the theory, people are more likely to find systems enjoyable if they believe them more beneficial (Teo et al., 1999). To explain the relationship between the two, Igbaria et al. (1995) also cited Bandura's self-efficacy theory (Bandura, 1986). Since self-efficacy significantly impacts emotion, PEOU can be viewed as self-efficacy, and PE can be regarded as a personal subjective emotion, it follows that PEOU will directly affect PE. Consequently, the following hypothesis is put forth in this paper:
H5: Perceived enjoyment has a significant impact on attitude.

2.4 Attitude

Attitude is the emotion one experiences after utilizing a technology, system, or service to carry out a desired behavior. As a result, attitude is the belief or negative emotion that a specific activity would transpire (Ajzen, 1991). As a result, attitude can be considered a factor influencing behavioral intention, mostly created through information gathering, reasoning, and observation (Bianchi et al., 2017). An attitude is a judgment or assessment of an individual's potential advantages or disadvantages of a particular course of action.

According to Davis et al. (1989), attitudes have little bearing on whether people accept new technologies. If the technology is helpful and simple, people are likely to employ it regardless of their neutral or negative sentiments toward it—technology to boost their output and effectiveness. Mathieson (1991) also discovered that eliminating the attitude component does not significantly affect the predictive power of the TAM.

It was abundantly evident by Davis et al. (1989) and Venkatesh and Morris (2000) that attitudes and behavioral intentions can be positively impacted by both PU and PEOU. Additionally, research has demonstrated that PEOU influences how popular and well-liked e-learning platforms are (Mailizar et al., 2021). According to Zogheib et al. (2015) research, PEOU also significantly improves attitudes regarding regional linkages, as indicated in below hypothesis:
H6: Attitude has a significant impact on behavioral intention.

2.5 Service Quality

According to Kotler and Keller (2014), service quality is determined by how well consumers' wants and expectations are met by the goods and services they receive. Furthermore, it must be made clear that service quality is not an objective measure of customers' satisfaction with goods or services but rather an assessment of the quality they perceive (Oliver, 2010). Hassan et al. (2013) defined service quality as the extent to which a service or general state is assessed or acknowledged.

The service quality theory by Parasuraman et al. (1985) service quality has grown in importance as a criterion for evaluating different industries. Because tourists are satisfied when the product or service level meets their expectations, many researchers in the tourism literature believe that service quality is important to tourist satisfaction and can be used as an indicator of it (Chen & Chen, 2010; Oliver, 2010; Udo et al., 2010; Zeithaml et al., 1993). In conclusion, SERVQUAL (Parasuraman et al., 1985) suggests that the gap between a customer's expectations and the service quality the service provider provides determines the degree to which the customer is satisfied with the quality of the service.

According to numerous research, PE has a beneficial impact on consumption (Liu & Liu, 2013). As an internal motivator, perceived enjoyment has been found to positively influence people's behavioral intentions and subsequent actions in several research (Davis et al., 1992; van der Heijden, 2003; Venkatesh & Speier, 1999; Venkatesh et al., 2002). Numerous research has examined the connection between reported satisfaction and varying degrees of new technology use (Igbaria et al., 1995; Teo et al., 1999;). A favorable functional link between the two is supported by most findings (Igbaria et al., 1995; Moon & Kim, 2001; Teo et al., 1999). The following presumptions are, therefore, also put out in the paper:
H7: Service quality has a significant impact on behavioral intention.

2.6 Social Influence

Social impact is a person's assessment and discernment of utilizing novel objects. According to a study by Wang and Zhu (2019), social influence promotes the spread of product/service usage scales. According to social influence, social influence is the extent to which individuals within a social network can affect one another's behavior (Rice et al., 1990). For instance, social influence (SI) in e-learning describes how much a learner supports or suggests that others utilize an e-learning platform after utilizing it. In UTAUT, Venkatesh et al. (2003) noted that in addition to performance expectation and effort expectation, social influence plays a significant role in influencing users' decisions to use information technology and form behavioral intentions based on how others perceive its importance. According to Fishbein and Ajzen (1975), the term "subjective norm" was originally used to describe social impact in the TRA model. Later theoretical investigations (Venkatesh et al., 2003) directly used social influence as a separate variable in UTAUT2. All this research demonstrates that social influence directly impacts behavioral intentions, though not always in a good way. Technology-related behavioral intentions are significantly influenced by social influence, an external incentive that makes up behavioral intentions (Wang & Zhu, 2019). (Singh et al., 2020). Considering these considerations, the premise of this work is as follows:

H8: Social influence has a significant impact on behavioral intention.

2.7 Behavioral Intention

According to Fishbein and Ajzen (1975), behavioral intention is "the degree of effort an individual makes to perform a specific behavior." It speaks to consumers' readiness to act practically to use, process, and utilize goods or services. As a result, behavioral intention also represents an individual's perceived likelihood of engaging in a certain behavior (Fishbein & Ajzen, 1975).

According to Trivedi and Yadav (2020), behavioral intentions significantly predict what customers do and can help forecast whether they will stay or depart. Additionally, Tuncer et al. (2020) defined behavioral intents based on whether clients have a positive assessment, are willing to stick with the goods or services, or freely suggest them to others. According to several definitions, behavior intention is the process by which an individual is prepared to try, accept, and foster customers' trust in an item to help them achieve their fulfillment.

3. Research Methods and Materials

3.1 Research Framework

According to Fishbein and Ajzen (1975) Theory of Reasoned Action (TRA) model, an individual's behavioral intentions are determined by their attitudes toward doing what they believe is right by people who matter to them. To sum up, The Theory of Planned Behavior (TPB) assumes that three main things influence people's actual behaviors and their behavioral intentions: personal attitudes, subjective norms, and perceived behavioral control.

When it comes to practical considerations, The Technology Acceptance Model (TAM) primarily examines internal factors. However, we also need to consider external factors like individual differences and values (like perceived values), convenience, and social influence (like subjective norms) (Malhotra & Galletta, 2003). In contrast, TPB emphasizes the influence of subjective norms, which is crucial for consumers because their actions will affect one another in society (Li et al., 2012). According to the TPB model, individual decisions are based on conjecture and prediction of behavioral consequences (Bamberg & Moser, 2007). As a result, behavioral attitudes, subjective norms, and perceived behavioral control all generate behavioral intentions.

Venkatesh et al. (2003) state that the Unified Theory of Acceptance and Use of Technology (UTAUT) model's greatest benefit is its ability to assist users in more accurately predicting the advantages and results of new technologies. Because UTAUT is a model that integrates several traditional theories, it is also widely employed in information technology research and plays a significant guiding function. The UTUAAT2 model was later established by Venkatesh et al. (2012) by extending the UTUAUT model. We will also refer to this model when studying for this paper. TAM, TPB, UTAUT, and its extended structure, UTAUT2, were combined. I then chose relevant factors for analysis and constructed this article's framework based on each model's benefits, consisting of seven fundamental factors: attitude, social influence, perceived usefulness, perceived ease of use, perceived enjoyment, service quality, and behavioral intention. Please refer to the diagram below to better understand the paper's structure.

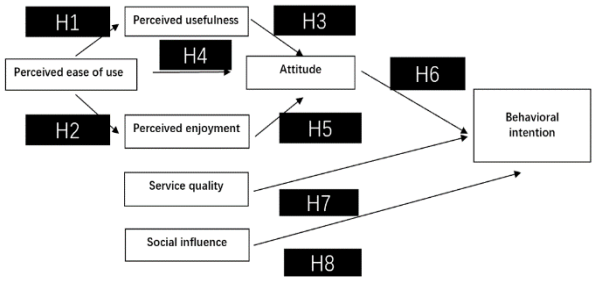

Figure 1: Conceptual Framework

H1: Perceived ease of use has a significant impact on perceived usefulness.
H2: Perceived ease of use has a significant impact on perceived enjoyment
H3: Perceived usefulness has a significant impact on attitude.
H4: Perceived ease of use has a significant impact on attitude.
H5: Perceived enjoyment has a significant impact on attitude.
H6: Attitude has a significant impact on behavioral intention.
H7: Service quality has a significant impact on behavioral intention.
H8: Social influence has a significant impact on behavioral intention.

3.2 Research Methodology

The researchers used the quantitative method of non-probability sampling and distributed questionnaires through the professional survey software Questionnaire Star, and the target respondents were undergraduate students in three universities in Chengdu, China. The influential factors affecting Chengdu college students' choice of live shopping methods were analyzed through data collection and collation. The survey consisted of three parts. Firstly, the target population was targeted by screening questions to meet the interview conditions. Second, a 5-point Likert scale was used to measure the five proposed variables, from "strongly disagree" (1 point) to "strongly agree" (5 points), to analyze and test all hypotheses. Finally, an expert's item-objective congruence (IOC) test was conducted through a pilot test with 50 respondents. The pilot study, yielded a Cronbach's Alpha score surpassing 0.7, affirming the reliable measurement of the designated construct and improving the overall reliability of the test results, aligning with the criteria outlined by Nunnally and Bernstein (1994).

The validity and reliability of the Cronbach's alpha method was tested. After the reliability test, the questionnaire was distributed to the target respondents, and 550 responses were received. Out of which 500 were valid responses. The researcher analyzed the collected data through SPSS. Confirmatory Factor Analysis (CFA) was then used to test the data for convergence, accuracy, and validation. The model fit metric was calculated by overall testing of the given data to ensure the validity and reliability of the model. Finally, the researchers applied Structural Equation Modelling (SEM) to test the specific effects of the variables.

3.3 Population and Sample Size

According to the research task and target of this paper, we want to explore the influencing factors of Chengdu college students' intention to livestream shopping behavior. Our target groups are Xihua University, Southwest Jiaotong University, and the University of Electronic Science and Technology of China. These three universities follow the Chinese higher education system. The divisions represent three highly representative levels. At the same time, the disciplines involved in the three universities are also rich and comprehensive. After the data screening process, 550 responses were used in this study, while the present study used 500 responses.

3.4 Sampling Technique

The researcher first used a non-probability sampling method and then quota sampling to determine the sample size based on the number of undergraduate students enrolled in each school, as shown in Table 1. Finally, the researcher used a convenience sampling method to collect data through an online questionnaire format. As of the latest data in July 2023, the relevant table of the target population is as follows:

Table 1: Sample Units and Sample Size

University	Population Size	Proportional Sample Size
Xihua University	38628	220
Southwest Jiaotong University	28914	165
University of Electronic Science and Technology	20234	115
Total	**87,776**	**500**

Source: Constructed by author

4. Results and Discussion

4.1 Demographic Information

For this questionnaire, the first choice is students from the three target colleges, and we can see that there are 273 female respondents, accounting for 54.6%, and 227 male respondents, accounting for 45.4%; according to the grades, there are a total of 129 students in the first year of college, accounting for 25.8%, 149 students in the second year of college, accounting for 29.8%, and 129 students in the third year, accounting for 25.8%. There are relatively fewer

participants in the fourth year of college because they have already completed all the courses. In the fourth year, the number of participants was relatively small due to completing all courses, with a total of 93 participants, accounting for 18.6%.

Table 2: Demographic Profile

Demographic and General Data (N=500)		Frequency	Percentage
Gender	Male	273	54.6%
	Female	227	45.4%
Undergraduate Year	Year 1	129	25.8%
	Year 2	149	29.8%
	Year 3	129	25.8%
	Year 4	93	18.6%

4.2 Confirmatory Factor Analysis (CFA)

Confirmatory factor analysis (CFA) was significant for this study. We can see that all items in each variable are significant and represent factor loadings. Their values can be tested for discriminant validity, and good significance and acceptable values for factor loadings represent goodness of fit (Hair et al., 2006). As can be seen from the table below, the factor loadings show between 0.701 and 0.810. The CR for each variable is greater than 0.823, and the AVE remains from 0.526 to 0.636. According to Fornell and Larcker (1981), the composite reliability must be greater than 0.7, while the average variance extracted value is greater than 0.5. Thus, each variable shown in the table below is significant

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

Variables	Source of Questionnaire (Measurement Indicator)	No. of Item	Cronbach's Alpha	Factors Loading	CR	AVE
Perceived Ease of Use (PEU)	Davis (1989)	6	0.901	0.787-0.810	0.913	0.636
Perceived Usefulness (PU)	Davis (1989)	4	0.850	0.745-0.805	0.852	0.590
Perceived Enjoyment (PE)	Davis et al. (1992)	4	0.820	0.728-0.739	0.823	0.537
Attitude (ATT)	Davis et al. (1989)	4	0.806	0.706-0.767	0.816	0.526
Service Quality (SQ)	Kotler and Keller (2014)	12	0.959	0.701-0.780	0.933	0.537
Social Influence (SI)	Wang and Zhu (2019)	3	0.832	0.776-0.804	0.833	0.625
Behavioral Intention (BI)	Fishbein and Ajzen (1975)	6	0.910	0.730-0.763	0.884	0.559

In addition, the CFA test used GFI, AGFI, NFI, CFI, TLI, and RMSEA as model fit indicators. From Table 4, this study's convergent validity and discriminant validity are greater than the acceptable values. Thus, both convergent validity and discriminant validity are validated and assured. Discriminant validity and validation were also demonstrated through these model measurements to ensure the model's validity for subsequent studies.

Table 4: Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	< 5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	1.745
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.894
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.878
NFI	≥ 0.80 (Wu & Wang, 2006)	0.894
CFI	≥ 0.80 (Bentler, 1990)	0.952
TLI	≥ 0.80 (Sharma et al., 2005)	0.948
RMSEA	< 0.08 (Pedroso et al., 2016)	0.039
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

Table 5 explains the square root value of the mean-variance extracted. The values were 0.798, 0.768, 0.733, 0.725, 0.733, 0.790, and 0.747, which are greater than 0.7, so they are significant and approve discriminant validity.

Table 5: Discriminant Validity

	PEU	PU	PE	ATT	SQ	SI	BI
PEU	**0.798**						
PU	0.548	**0.768**					
PE	0.472	0.486	**0.733**				
ATT	0.567	0.646	0.527	**0.725**			
SQ	0.231	0.102	0.156	0.236	**0.733**		
SI	0.401	0.171	0.158	0.198	0.285	**0.790**	
BI	0.373	0.298	0.289	0.498	0.461	0.559	**0.747**

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

4.3 Structural Equation Model (SEM)

According to Hair et al. (2010), Structural Equation Modelling (SEM) validates the measurement error of the causal relationships between variables in the proposed model. The goodness-of-fit indices of the structural equation modeling are shown in Table 5.2. According to Greenspoon and Saklofske (1998), the GFI and CFI should be higher than 0.8. Every statistic value is satisfied with the acceptable value. Their respective values are 1.925 (less than 5.00), 0.881 (greater than 0.85), 0.866 (greater than 0.80), 0.881 (greater than 0.80), 0.935 (greater than 0.80), 0.939 (greater than 0.80), 0.043 (less than 0.08).

Table 6: Goodness of Fit for Structural Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/ DF	< 5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	1.925
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.881
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.866
NFI	≥ 0.80 (Wu & Wang, 2006)	0.881
CFI	≥ 0.80 (Bentler, 1990)	0.935
TLI	≥ 0.80 (Sharma et al., 2005)	0.939
RMSEA	< 0.08 (Pedroso et al., 2016)	0.043
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

The research model was calculated using regression weights for each variable and R2 significance of variance. The results in Table 6 show that β of H1 is 0.559, β of H2 is 0.486, β of H3 is 0.421, β of H4 is 0.227, β of H5 is 0.238, β of H6 is 0.385, β of H7 is 0.315, β of H8 is 0.441 with the positive results supported.

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-value	Result
H1: PEU→PU	0.559	10.886*	Supported
H2: PEU→PE	0.486	9.088*	Supported
H3: PU→ATT	0.421	7.177*	Supported
H4: PEU→ATT	0.227	3.762*	Supported
H5: PE→ATT	0.238	4.458*	Supported
H6: ATT→BI	0.385	7.830*	Supported
H7: SQ→BI	0.315	7.007*	Supported
H8: SI→BI	0.441	8.809*	Supported

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

The result from Table 7 can be refined that:

H1 shows a strong correlation between PEU and PU with a T-value of 10.886, which corresponds with the study of Mao and Palvia (2006); perceived ease of use also positively impacts perceived usability. According to Venkatesh and Davis (2000), the easier a particular technology is, the more useful it is. In other words, when individuals find a technology/service easy to use, users will be more likely to recognize the technology/service and acknowledge its positive effects. Regarding H2, the T-value is 9.088, which supports the correlation often appearing in the technology acceptance motivation model proposed by Deci (1975) or Davis (1989). The idea is that systems individuals perceive as more useful are also more likely to be pleasurable (Teo et al., 1999). H3 and H2 are effective in the same model with the same result. H4 is also supported by Early research that found that PEU positively affects attitude (Lin & Lu, 2011); some studies have confirmed a direct relationship between perceived usefulness and attitudes (Krishnan et al., 2016). H5 measures the relationship between PE and ATT, which is confirmed by Kim and Forsythe (2008), who claim that perceived usefulness (PU) and perceived ease of use (PEOU) jointly affect individuals' attitudes toward the use of technology. For H6, the T-value is 7.830, which means attitude positively influences behavioral intention; this can be seen in the research of Solomon (2004); attitude is an important variable to explain behavioral intention, and it has the greatest and most direct impact on behavioral intention. H7 shows the correlation between SQ and BI with the T-Value 7.007, Zeithaml and Bitner (1996) believed that service quality unidirectionally affects behavioral intentions. The last H8 is verified with 8.809, well supported by Wang et al. (2019), who said that social influence, as an external motivation, constitutes behavioral intentions and largely affects technology-related behavioral intentions.

5. Conclusion and Recommendation

5.1 Conclusion

This research paper focuses on the factors influencing the behavioral intentions of live shopping on students (undergraduate students) attending university in Chengdu. The paper proposes eight major hypotheses through seven variables. Through a questionnaire survey in Chengdu, this study selected three very representative schools; they represent different levels of education, according to the different undergraduate student data in each school, according to the proportion of screening, and finally, they took the effective sample of 500. The data analysis aimed to explore whether these factors influence students' behavioral intentions and how they do so. Therefore, Confirmatory Factor Analysis (CFA) was successively conducted to measure and test the conceptual model's validity and reliability. Each factor was then analyzed using structural equations, and the whole model was analyzed by SEM, which produced positive results.

The findings of the study are as follows. Firstly, Attitude, Social Influence, and Service Quality directly influence behavioral intention, and PEU, PU, and PE indirectly influence behavioral intention through attitude. Social influence has the greatest degree of influence on students' use of livestream shopping. Many studies have confirmed the importance of social influence on consumer behavior. According to Martins et al. (2014), social influence produced a strong, positive predictor of behavioral intentions regarding Internet banking acceptance and usage. Secondly, the attitudes of undergraduate student consumers toward

live-streaming shopping have a definite positive impact on their behavioral intentions. Most research confirms a strong link between attitudes and behavioral intentions (Martins et al., 2014). Taylor and Todd (1995) state that user attitudes reflect preferred choices about using a particular technology. Thirdly, the quality of service of live shopping also greatly influences this group's behavioral intentions. In empirical studies, researchers emphasize that service quality is the customer's perception of the difference between what they see and actually feel. This conclusion is also entirely consistent with the SERVQUAL model proposed by Parasuraman et al. (1988), which states that service quality almost equals core competitiveness.

Finally, it pinpoints the three indirect influences and how they interact and work together. The results show that PU directly influences users' attitudes towards live shopping, followed by PE and PEU. However, PEU itself has a direct influence on both PU and PE. The relationship between the three is difficult to define clearly. Regarding the original construction of TAM, PEOU can be seen as a precursor to PU (Davis, 1989; Venkatesh & Davis, 2000). In Chung et al. (2015) study, the authors also explicitly tested users' behavioral intention of mobile English vocabulary learning resources. It was positively correlated with PE and PEOU. Also, there is a positive correlation between the two. Therefore, the conclusion is clear that the direct and indirect influences, as well as the positive influences, are presented objectively, in line with the initial research objectives of this paper. That is, the social influence of word-of-mouth is the most direct and obvious influencing factor, and the attitude toward live shopping and the quality of its own service also greatly influences the intention of Chengdu University students' consumption behaviors.

5.2 Recommendation

The researcher found out that the important factor influencing college students to have the intention to shop through live streaming is social influence, hence the importance of word of mouth, where a person who has a good experience with the sense of use will consciously recommend it to others. On the contrary, even if the adverts are all over the place but the experience feels poor, then a person will pass on negative feelings to others. So, in this process, people are the most important factor; not only the importance of audience but also the people who are leading the livestream shopping behaviors are also important. Therefore, there is a need to continuously develop new technologies and improve the quality and level of service to meet consumers' different needs and tastes. Social influence, as an external motivator that constitutes behavioral intentions (Wang et al., 2019), influences technology-related behavioral intentions to a large extent (Singh et al., 2020). In the study of Abbasi et al. (2012), if it is true that the promotion and use of new technologies are influenced by social influence and that individuals change their behaviors based on the choices and behaviors of others, then social influence does play an absolute role in the promotion and use of new technologies.

5.3 Limitation and Further Study

The limitations of this study are, firstly, as far as the study population is concerned, the sample was randomly answered online through Questionnaire Star in three universities in PI District, Chengdu City. Only the teaching level of the three colleges was considered, but not a more balanced distribution regarding geographical location. Secondly, the research on the influencing factors can be expanded to include the relationship between service quality and social impact and the impact situation. As a new thing in the context of the Internet, the role of service quality on social influence is direct and important to the naked eye. Finally, Fishbein and Ajzen (1975) believed that the TRA model first used the term "subjective norm" to explain social influence. It is possible to refine the study of subjective norms.

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