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Original Article

Consumer Intention and Usage Behavior of Live-Streaming Shopping: An Extension of the Unified Theory of Acceptance and Use of Technology

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Abstract

Live-streaming shopping is increasing in both popularity and profitability throughout the world. However, there are limited studies that have focused on the psychological motivation of customers regarding information technology for live-streaming shopping behavior. Grounded in the unified theory of acceptance and use of technology-2 model, this study was the first to include trust, perceived risk, deal proneness, and consumer innovativeness simultaneously to examine consumer intention and usage behavior of live-streaming shopping. Additionally, the moderating effects of demographic characteristics involving gender, age, and experience were included. A convenience sampling method was used to gather data from 860 Chinese live-streaming users in mainland China. The Cronbach's alpha coefficient showed overall scale reliability was .97. The results of PLS-SEM analysis confirm that the present model has a medium capacity to explain behavioral intention (R^2 = .47) and usage behavior (R^2 = .50). Besides, "habit" has been found as the strongest predictor of both behavior intention (β = .28, p < .001) and actual use (β = .32, p < .001) of live-streaming shopping. The finding suggests the importance to encourage consumers to use live-streaming shopping. Interestingly, the results provide valuable insights that can be applied by vendors to enhance intention to use live-streaming shopping among consumers by improving and retaining their hedonic motivation and trust.

Live-streaming shopping has become a new method of online shopping around the world. The sales in live-streaming platforms are on a continuously increasing trend, and their market share in China is growing rapidly (Wongkitrungrueng & Assarut, 2020). The live-streaming e-commerce market in China reached about 1237.9 billion yuan (approximately 175.71 billion U.S. dollar), increasing from 120 billion yuan (approximately 17.03 billion U.S. dollar) in 2018 (Ma, 2021). Thus, this research was conducted in the context of China. The China Internet Network Information Center (2022) reports that there were 703 million live-streaming users in China at the end of 2021. Among them, the users of live-streaming e-commerce attained 464 million, which accounts for 44.9 percent of the total internet users. With the increase in the number of live-streaming users, live-streaming platforms have been transformed into a common sales channel and marketing strategy in the e-commerce market. Live-streaming e-commerce covers products and services of all industries, such as agricultural products, home appliances, life appliances, cosmetics, etc., that activate the consumption potential and promote the resumption of production and rehabilitation during the COVID-19 pandemic (Chen, 2021). In 2020, the gross merchandise value (GMV) of live-streaming e-commerce achieved 1237.9 billion yuan (approximately 175.75 billion U.S. dollars) in China (Ma, 2022a). To date, the GMV of live-streaming e-commerce in

China accounted for 20.1% of the total GMV of online shopping in 2022 (Ma, 2022b). In the digital economy, live-streaming in e-commerce has become one of several marketing tactics.

The rapid development of live-streaming platforms attracts plentiful academic and empirical attention. For instance, some studies were conducted for exploring the development, categories, and characteristics of live-streaming platforms (Chen 2021; Wang et al., 2021; Zhang et al., 2021). Several previous studies investigated live-streaming shopping from the consumer perspective, such as impulse buying behavior (Wu & Chin, 2021; Xu et al., 2020), purchase intention (Sun et al., 2019; Zhao & Bacao, 2021), utilitarian and hedonic motivation (Cai et al., 2018), and shopping decisions (Wang et al., 2021). However, there are a limited number of studies that have focused on consumer psychological motivation with information technology. To the author's knowledge, so far only Zhou et al. (2021) investigated the psychological motivations of consumers for live-streaming shopping behaviors. Previous studies have emphasized that live-streaming shopping is a sort of human-computer interaction (Sun et al., 2019; Yang et al., 2022; Zhao & Bacao, 2021); thus, the extended unified theory of acceptance and use of technology (UTAUT2) is an appropriate framework for investigating the mechanisms that influence consumer online buying behavior. It has been confirmed that the UTAUT2 model increases the percentage of variation explained in the intention to use information and communication technologies by 18% and the percentage of variance explained in the actual usage of ICT by 12% (Venkatesh et al., 2012). Likewise, UTAUT2 shows strong explanatory power and is extensively applied in the field of consumer behavior, involving online shopping and mobile-based shopping (Chopdar & Sivakumar, 2019; Escobar-Rodríguez & Carvajal-Trujillo, 2014; Tak & Panwar, 2017; Zhou et al., 2021;), in-store smartphone usage (Mosquera et al., 2018), mobile banking (Çera et al., 2020), online hotel booking (Chang et al., 2019), online travel purchases (Sharma et al., 2020), and communication technology applications (Castanha & Pillai, 2021). However, very few prior studies have adopted it in the context of live-streaming shopping.

To conclude, few studies have focused on consumer psychological motivation with information technology for live-streaming shopping behavior by adopting the UTAUT2 model. Besides, this research was the first to include trust (Zhang et al., 2021; Zhao & Bacao, 2021; Zhou et al., 2021), deal proneness (Tak & Panwar, 2017), perceived risk (Chopdar & Sivakumar, 2019; Wen & Cai, 2014; Xu, 2021) and consumer innovativeness (Escobar-Rodríguez & Carvajal-Trujillo, 2014) simultaneously in the UTAUT2 model. In addition, China is considered an appropriate research context for investigating live-streaming shopping, given that the scale of live-streaming e-commerce exceeded a trillion yuan in 2020 (Chen, 2021). Even Venkatesh et al. (2012) proposed that the moderating effects of individual demographics were not included in the relationship between effort expectancy, performance expectancy, and social influence on behavioral intention. Many studies have demonstrated that there are substantial discrepancies between different individual demographics in the UTAUT2 model (Mosquera et al., 2018; Zhao & Bacao, 2021; Zhou et al., 2021). Therefore, the moderating effects of demographic constructs, experience, age, and gender, were also included in this study.

Based on the review of previous studies, the purpose of this study is to offer a more complete model in the context of live-streaming shopping. This study adds contribution to the current literature of UTAUT2 extension as well as the enrichment of theoretical analysis on understanding consumer intention and actual behavior of live-streaming shopping. Besides, the outcomes of this study have some managerial consequences for live e-commerce vendors by proposing marketing and promotion tactics regarding live-streaming shopping.

Literature Review

In this section, relevant literature and previous studies will be discussed. Additionally, live-streaming shopping, the UTAUT2 model, and hypotheses development are discussed as well.

Live-Streaming Shopping

Live-streaming is a novel form of social media activity that includes content such as gaming, selling, or sharing in which streamers simultaneously transmit multimedia content online to viewers (Wu & Chin, 2021). A series of recent studies have indicated that live-streaming shopping is differentiated from traditional online shopping in several ways. First, buyers can only see the goods through images and text in conventional internet buying. In comparison, live-streaming shopping enables merchants to introduce, show, explain, and promote goods or services synchronously via live video, thus providing clients with more specific information regarding the products or services (Cai et al., 2018; Chen, 2021; Sun et al., 2019; Wu et al., 2021). Second, buyers must exit the product page to approach the vendor with questions about that product in conventional social commerce. However, live-streaming shopping allows consumers to raise issues through a bullet screen, and then merchants can communicate and interact with them to respond to those questions in real-time (Chen, 2021; Sun et al., 2019; Wu & Chin, 2021; Wu et al., 2021). Last, live-streaming shopping incorporates entertaining aspects by utilizing key opinion leaders as hosts, so consumers become more responsive to new information and products in a stimulating atmosphere (Wang et al., 2021; Zhang et al., 2021).

Theoretical Framework for the Research

Generally speaking, despite the fact that these empirical and theoretical investigations have improved people's comprehension of the adoption along with usage of user acceptance of new technologies in the consumer use context, there are still certain significant phenomena that demand more explanation in the context of live-streaming shopping in China. Firstly, trust is always a concern in the online shopping environment from the viewpoint of consumers. Various adoption models have included trust as a crucial factor in the analysis of usage intentions including UTAUT2 (Zhao & Bacao, 2021). Earlier literature stated that the initial trust can be improved by reducing perceived risk in automated vehicles (Zhang et al., 2019). Perceived risk is an assessment of unanticipated dissatisfaction and disappointment with purchasing decisions based on the purchase objective (Donni et al., 2018). From the perspective of consumers, purchasing online is riskier than buying in a brick-and-mortar store (Ariffin et al., 2018). Therefore, perceived risk plays an important role in determining consumer purchase intentions. Next, consumer propensity to react to promotions is characterized as deal proneness (Rakesh & Khare, 2012), which refers to consumer growing preference for deals while purchasing goods or services (Lichtenstein et al., 1990). Previous studies confirmed that price discounts demonstrated a significant effect on consumer purchase intention (Xu et al., 2020; Zhong et al., 2022). Lastly, Venkatesh et al. (2012) considered the differences in consumer innovativeness and thus proposed that the effect of hedonic motivation on behavioral intention can be moderated by individual demographics. Escobar-Rodríguez and Carvajal (2014) conducted a study based on the UTAUT2 model to investigate purchasing low-cost airline tickets online. By including consumer innovativeness and customer trust, their study found that these factors significantly impact consumer intention to buy low-cost flight tickets online.

Hypotheses Development

Regarding consumer attitudes and engagement when purchasing live online, this study proposes hypotheses rooted in the extended UTAUT2 model.

Performance expectancy is defined as the extent to which customers will gain from utilizing technology when engaging in particular activities (Venkatesh et al., 2012). Performance expectancy adapted to live-streaming shopping considers how consumers view the advantages they get from using live-streaming platforms for shopping. In the current study, for instance, reducing time, shopping efficiently, and having a look for the right merchandise are examined. This construct was significantly manifested as the determinator of behavioral intention in prior studies, e.g., live-streaming shopping (Zhou et al., 2021), mobile shopping (Hanif et al., 2022; Tak & Panwar, 2017), and mobile payment (Widyanto et al., 2020). Therefore, H1 is proposed:

H1: Performance expectation will positively impact behavioral intention.

Effort expectancy is viewed as the extent of the accessibility of using technology by consumers (Venkatesh et al., 2012). It is a similar construct to the perceived ease of use in the Technology Acceptance Model (Davis et al., 1989), which has been confirmed to have a substantial impact on people's decision to engage in online social commerce (Ying et al., 2021), online shopping (Nagy & Hajdú, 2021), and mobile banking (Mahakunajirakul, 2022). In this study, effort expectancy involves ease of utilizing, selection, payment method, and interaction of live-streaming shopping. In addition, this construct was found as a major determinant of purchase intention in the context of online shopping (Hanif et al., 2022; Zhou et al., 2021). According to earlier studies, H2 is proposed:

H2: Effort expectation will positively impact behavioral intention.

Social influence refers to the extent to which users perceive those significant persons, such as friends and family, think they should adopt a certain technology (Venkatesh et al., 2012). Family, friends, colleagues, supervisors, key opinion leaders, and social tendencies are included in the current study for social influence. The experience from significant persons will affect consumer shopping intention to live-streaming shopping. Previous literature mentions that social influences is a key factor in online purchases in Vietnam (Doan, 2020), mobile shopping in Pakistan (Hanif et al., 2022) and in India (Tak & Panwar, 2017), mobile banking usage in Albania (Çera et al., 2020), and internet banking services in Gujarat (Patel & Patel, 2018). Thus, H3 is presented:

H3: Social influence will positively impact behavioral intention.

Facilitating conditions are related to consumer perceptions of the numerous support and resources they can use to carry out the desired behavior (Venkatesh et al., 2012). This construct has demonstrated that it affects behavioral intention as well as usage behavior according to the UTAUT2 model (Chopdar & Sivakumar, 2019; Hanif et al., 2022; Mosquera et al., 2018). The adoption of live-streaming shopping, mobile devices, channels of payment, the internet, personal knowledge, and assistance from others are included in the facilitating conditions in the current study. Therefore, the hypotheses are proposed:

H4: Facilitating conditions will positively impact behavioral intention.

H5: Facilitating conditions will positively impact usage behavior.

Hedonic motivation is regarded as the enjoyment or pleasure gained while using a technology (Venkatesh et al., 2012). Falode et al. (2016) stated hedonic shopping is a fantastic shopping experience in which customers may have a satisfying emotional reaction to the activity whether or not they make a purchase. Compared to traditional online shopping, live-streaming shopping combines entertaining aspects by having KOLs in the event (Wang et al., 2021). Thus, H6 is put forward:

H6: Hedonic motivation will positively impact behavioral intention.

Price value refers to the consumer recognized trade-off between the applications' ostensible advantages and their monetary costs (Mosquera et al., 2018; Zhou et al., 2021). It is a significant difference between the context of consumer use and organizational use, where UTAUT was developed (Venkatesh et al., 2012). A previous study has shown the significant effect of price value on the continuance intention of mobile shopping applications (Chopdar & Sivakumar, 2019). Therefore, H7 is posited:

H7: Price value will positively impact behavioral intention.

Habit represents the feedback from prior experiences and is thus tied to consumer decisions to utilize novel technology, both in terms of behavioral intent and actual usage behavior (Zhou et al., 2021). A cross-cultural study by Merhi et al. (2019) found that consumer habit was the strongest antecedent to the behavioral intention towards utilization of mobile banking services for both Lebanese and English consumers. In addition, Droogenbroeck and Hove (2021) showed that habit influenced both use intention and the actual use of online grocery shopping in Belgium. The below hypotheses are presented:

H8: Habit will positively impact behavioral intention.

H9: Habit will positively impact usage behavior.

Consumer innovativeness has been extensively studied in the context of consumer behavior because it demonstrates an individual's proclivity or desire to explore new products and services (Roehrich, 2004). That is, customers with a high level of innovativeness are inherently interested, appreciate creative discovery, and, as a result, are more likely to adopt new products/services (Choo et al., 2014). Venkatesh et al. (2012) stated that an enhancement in hedonic motivation to utilize any product can derive from such innovativeness. Although some studies have investigated the influence of consumer innovativeness on the live-streaming shopping intention, to gain additional empirical evidence and prospect a more comprehensive framework, it is necessary to involve this factor in the current study. Therefore, the hypotheses are:

H10: Consumer innovativeness will positively impact behavioral intention.

H11: Consumer innovativeness will positively impact usage behavior.

Trust is an individual’s subjective assessment of another person or company's trustworthiness, honesty, consistency, and aptitude (Alalwan et al., 2017). Internet technology is currently being widely used by consumers for sensitive information-related tasks (Venkatesh et al., 2016). Thus, trust is an extremely important concept that is usually applied to be a determinant for influencing both behavioral intention and usage behavior in various fields, especially in the electronic context. Even though prior research has proven the important role of trust in both behavioral intention and usage behavior in online shopping, it is still essential to be involved in the context of live-streaming shopping. As a consequence, two hypotheses were presented:

H12: Trust will positively impact behavioral intention.

H13: Trust will positively impact usage behavior.

Perceived risk is identified as one of the major motivators in consumer behavior. Previous research findings demonstrate that a high level of perceived risk seems to be negatively correlated with consumer trust in online activities (Ariffin et al., 2018; Yang et al., 2015). However, customers would decide to trust a vendor if the perceived risk was kept within a specified range (Hong, 2015). Customers properly choose online vendors to make a purchase that are reliable enough to minimize perceived risk. Besides, the positive relationship between perceived risk and trust has been confirmed in online purchase intention (Ling et al., 2011) and online merchant selection (Hong, 2015). In this regard, this study hypotheses:

H14: Perceived risk will positively impact trust.

H15: Perceived risk will positively impact behavioral intention.

Deal proneness is a psychological concept that influences behavior related to value awareness and coupon responsiveness (Lichtenstein et al., 1990). A deal-prone consumer considers the psychological advantages of closing the deal and may not be bothered by the financial repercussions (Tak & Panwar, 2017). Martínez-López et al. (2014) mentioned that the accessibility of instruments for price comparison encourages customers to purchase online instead of through traditional methods. Therefore, online merchants apply a lot of promotions to attract customers to participate in activities or purchase consumption, and even online shopping platforms come up with all kinds of festivals to stimulate consumption (Chen & Li, 2020; Vakeel et al., 2018).

H16: Deal proneness will positively impact behavioral intention.

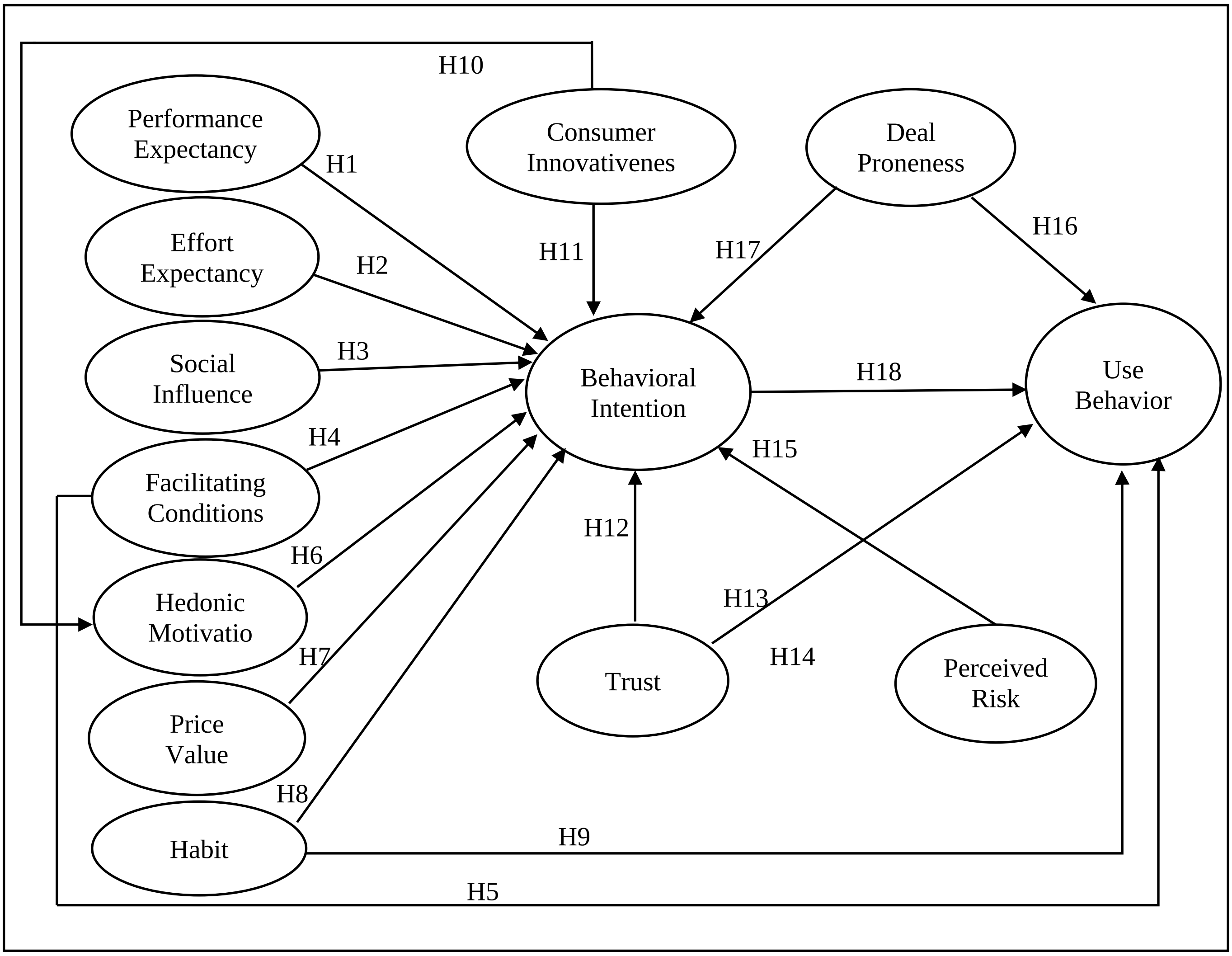
H17: Deal proneness will positively impact usage behavior.

Lastly, there is sufficient evidence to support a strong association between behavioral intention and usage behavior (Mosquera et al., 2018; Tak & Panwar, 2017; Zhou et al., 2021). Thus, the last hypothesis was:

H18: Behavioral intention will positively impact usage behavior.

According to the above considerations, this study aims to test a conceptual model rooted in UTAUT2 to explore the influencing factors that affect consumer intention and usage behavior of live-streaming shopping (as shown in Figure 1).

Figure 1
Proposed Hypothesized Model



Method

Participants

This quantitative research conducted primary data collection via an online questionnaire. Participants in this study were online shopping or live-streaming shopping users throughout mainland China. To assess the compatibility of potential respondents, one pre-screening question was included to ask respondents if they had experience in live-streaming shopping. Only those who answered having a particular experience were given access to the questionnaire. By the end of June, there were 33 infections of COVID-19 in China (National Health Commission of the People's Republic of China, 2022). It was difficult to conduct an on-site survey in the mainland of China; therefore, a convenience sampling method was applied. Based on a convenience sampling method, the questionnaires were distributed online and via WeChat for collecting data from June 30th to July 10th, 2022. WeChat is one of the largest social media applications in China (Yang et al., 2021). Some participants were recruited through private messages, and others were recruited by the researcher's students by sharing a link containing the questionnaire through WeChat Moments and WeChat group.

Hair et al. (2011) state that partial least squares structural equation modeling (PLS-SEM) requires a sample size that is more than ten times the maximum number of inner or outer model linkages that can point to any given latent variable. In this study, there are twelve linkages pointing to the latent variable of behavior intention, so the sample size requirement is 120. On July 10, 2022, 969 empirical data were obtained. After filtering out the untrustworthy responses, 860 valid responses were collected. The sample size of the current study reaches the statistical requirements of the formula. Among the 860 respondents, 319 (37.1%) were male and 541(62.9%) were female. In addition, 581 (67.6%) respondents were born in or before the year 2000, and 279 (32.4%) respondents were born after the year 2000. Lastly, 185 (21.5%) respondents had less than one year of experience with live-streaming shopping, 428 (49.8%) had 1-3 years, 204 (23.7%) had 4-6 years, and 43 (5%) had above 7 years.

Instruments

A quantitative methodology was utilized to examine the proposed model in this study. An online self-administered questionnaire was conducted to gather data, which included two sections. The first section was demographic data that includes gender, age, and experience of applying live-streaming shopping; the second part involved a 7-point Likert scale (from 1 = strongly disagree to 7 = strongly agree) for measuring the psychological perception of the respondents with fifty-two items, which were adapted from Çera et al. (2020), Escobar-Rodriguez and Carvajal-Trujillo (2014), Venkatesh et al. (2012), Xu et al. (2021), and Zhou et al. (2021). The questionnaires were written in the Chinese language through a back-translation method (Behr, 2017) since the population of this study was Chinese. In addition, a pilot study of 23 sample subjects was conducted to ensure the feasibility of the Chinese version of the questionnaire. The results of Cronbach's alpha show the reliability of the overall questionnaire was .97. Additionally, the reliability and validity were measured by Cronbach's alpha (CA), composite reliability (CR), and average variance extracted (AVE). The findings illustrated that all constructs met the threshold of CA of .7, CR of .7, and AVE of .5 (Hair et al., 2019) as Table 1 presents.

Ethical Considerations

This study has been carefully reviewed and approved by the research ethics committee of International College, National Institute of Development Administration, Thailand, in the meeting of Agenda NIDA International College Board No. 2/2565, on June 30, 2022, along with reference number "event 4.1_2".

Table 1
Construct Reliability and Validity of Pilot Study

Constructs	Number of Items	CA	CR	AVE
Performance expectancy	4	.93	.95	.83
Effort expectancy	4	.88	.92	.74
Social influence	5	.84	.89	.61
Facilitating conditions	5	.86	.90	.64
Hedonic motivation	4	.88	.91	.73
Price value	5	.86	.90	.65
Habit	4	.94	.96	.84
Trust	5	.85	.89	.63
Perceived risk	3	.93	.92	.78
Consumer Innovativeness	3	.87	.92	.79
Deal proneness	3	.94	.96	.89
Behavioral intention	4	.97	.98	.92
Usage behavior	3	.95	.97	.90

Results

Partial Least Squares Structural Equation Modeling (PLS-SEM) was applied to measure the proposed model because it is more in line with the study objectives. On one hand, the proposed model is complex by containing 18 hypotheses, and PLS-SEM enables coping with highly complex models; on the other hand, this statistical method is suitable for exploratory research and theory development (Hair et al., 2019). Therefore, SmartPLS 3.2.9 (Ringle et al., 2015) was used to analyze this study.

Analysis of the Measurement Model

Before the structural model assessment, all the required criteria should be satisfied (Hair et al., 2019). The reliability and validity of the measurement model were measured as follows: the factor loadings, Cronbach's alpha (CA), composite reliability (CR), average variance extracted (AVE), and discriminant validity as illustrated in Table 2, Table 3 and Table 4.

Firstly, factor loadings were calculated to check the indicator's reliability, in which the loadings should be above .708 and significant at the .05 level (Urbach & Ahlemann, 2010; Hair et al., 2019). In the meanwhile, cross-loadings were measured, and the findings presented that the loading of each indicator was greater for its stipulated construct than for any of the other constructs (Urbach & Ahlemann, 2010). Next, CA and CR were tested to assess the quality of construct internal consistency reliability, and the findings show that all of the metrics exceed the required threshold of .70 (Hair et al., 2019). Besides, convergent validity was measured by AVE and all values were above the accepted level of .5 (Hair et al., 2019). Lastly, two methods were used to assess discriminant validity. Fornell-Larcker criterion (Fornell & Larcker, 1981) was applied as the first method, thus Table 3 presents that the square root of AVEs exceeds their correlation coefficient of other constructs, which meets the threshold of discriminant validity. Because the first method of Fornell-Larcker of PLS can overestimate the indicator loadings and underestimate the structural model relationships (Henseler et al., 2014), the Heterotrait-Monotrait (HTMT) ratio of correlation, a higher boundary criterion, was applied for testing the discriminant validity as the second method. All HTMT ratio test outcomes were lower than a threshold of .85 (Hair et al., 2019), which means the discriminant validity was satisfactory because all constructs were independent of each other.

Multicollinearity and Common Method Bias Assessment (CMB)

Full variance inflation factor (VIF) statistics were applied to check multicollinearity, and the findings show a range of the full VIFs with latent variables from 1.42 to 1.93, which are not higher than 3. In short, it proves there was no problem with multicollinearity (Hair et al., 2019). In addition, two methods were used to evaluate CMB. The first method is Harman's single-factor test. The current study assessed all indicators of the model by extracting a certain number of factors as a single factor. The finding was that the one-factor solution presented only 40.98% of the variance, which is lower than a threshold of 50% (Sun et al., 2019). The second method followed a marker technique that includes a theoretical irrelevant marker variable in the analysis (Venkatesh et al., 2012). The result shows no significant relationship between the marker variable and endogenous latent constructs. In conclusion, CMB is not a core issue in this study.

Table 2

Construct Reliability and Validity

Constructs	Number of Items	CA	CR	AVE
Performance expectancy	4	.94	.96	.84
Effort expectancy	4	.92	.95	.82
Social influence	5	.94	.96	.81
Facilitating conditions	5	.95	.96	.84
Hedonic motivation	4	.93	.95	.83
Price value	5	.95	.96	.84
Habit	4	.95	.96	.86
Trust	5	.96	.97	.85
Perceived risk	3	.95	.97	.90
Consumer Innovativeness	3	.93	.96	.88
Deal proneness	3	.95	.97	.91
Behavioral intention	4	.95	.96	.86
Usage behavior	3	.94	.96	.89

Table 3

Construct Reliability, Validity and Factor Loadings

Constructs	Items	Loadings	Constructs	Items	Loadings	Constructs	Items	Loadings
Behavioral Intention	BI1	.97 (232.92)	Effort Expectancy	EE1	.95 (143.50)	Perceived Risk	PR1	.97 (253.37)
	BI2	.908 (144.49)		EE2	.91 (113.63)		PR2	.95 (202.20)
	BI3	.91 (118.89)		EE3	.86 (62.91)		PR3	.93 (136.44)
	BI4	.93 (165.07)		EE4	.89 (91.09)	Performance Expectancy	PE1	.94 (132.90)
Consumer Innovativeness	INT1	.95 (200.12)	Deal Proneness	DP1	.97 (332.67)		PE2	.92 (150.84)
	INT2	.93 (167.46)		DP2	.94 (163.85)		PE3	.91 (122.50)
	INT3	.93 (154.83)		DP3	.95 (203.03)		PE4	.90 (112.77)
Habit	HA1	.965 (309.64)	Hedonic Motivation	HM1	.95 (190.54)	Usage behavior	UB1	.95 (178.42)
	HA2	.90 (116.37)		HM2	.91 (126.62)		UB2	.94 (155.76)
	HA3	.94 (245.04)		HM3	.88 (74.70)		UB3	.95 (213.86)
	HA4	.91 (123.13)		HM4	.89 (89.90)			
Facilitating Conditions	FC1	.97 (235.13)	Price Value	PV1	.96 (232.34)			

Table 3 *(Continued)*

Constructs	Items	Loadings	Constructs	Items	Loadings	Constructs	Items	Loadings
	FC2	.92 (95.42)		PV2	.91 (142.27)			
	FC3	.92 (121.64)		PV3	.91 (106.37)			
	FC4	.91 (108.10)		PV4	.89 (84.95)			
	FC5	.87 (79.44)		PV5	.92 (140.42)			
Social Influence	SI1	.94 (152.52)	Trust	TR1	.96 (215.07)			
	SI2	.91 (125.74)		TR2	.92 (165.37)			
	SI3	.87 (72.41)		TR3	.92 (149.96)			
	SI4	.91 (124.85)		TR4	.90 (109.49)			
	SI5	.88 (86.95)		TR5	.91 (128.03)			

Note. value within () is the value of T-statistics. BI = behavioral intention, INT = consumer innovativeness, DP = deal proneness, EE = effort expectancy, FC = facilitating conditions, HA = habit, HM = hedonic motivation, PR = perceived risk, PV = price value, SI = social influence, TR = trust, UB = usage behavior.

Table 4
Correlation of Constructs

	BI	INT	DP	EE	FC	HA	HM	PR	PE	PV	SI	TR	UB
BI	**.93**												
INT	.42 (.45)	**.94**											
DP	.42 (.45)	.42 (.45)	**.95**										
EE	.41 (.43)	.36 (.39)	.45 (.48)	**.90**									
FC	.37 (.39)	.33 (.35)	.49 (.51)	.49 (.52)	**.92**								
HA	.59 (.62)	.46 (.49)	.35 (.37)	.40 (.42)	.30 (.31)	**.93**							
HM	.48 (.51)	.38 (.40)	.42 (.44)	.41 (.44)	.32 (.33)	.47 (.50)	**.91**						
PR	.37 (.39)	.30 (.32)	.43 (.45)	.34 (.36)	.44 (.46)	.29 (.31)	.34 (.36)	**.95**					
PE	.44 (.47)	.38 (.41)	.41 (.44)	.44 (.47)	.40 (.42)	.45 (.48)	.43 (.46)	.37 (.39)	**.92**				
PV	.44 (.46)	.39 (.42)	.42 (.45)	.39 (.41)	.45 (.47)	.48 (.50)	.40 (.43)	.32 (.34)	.48 (.50)	**.92**			
SI	.52 (.55)	.44 (.46)	.39 (.42)	.43 (.46)	.37 (.39)	.56 (.59)	.52 (.55)	.38 (.40)	.48 (.51)	.46 (.49)	**.90**		
TR	.52 (.55)	.38 (.40)	.42 (.44)	.44 (.46)	.40 (.42)	.57 (.60)	.51 (.54)	.35 (.36)	.46 (.48)	.48 (.50)	.52 (.55)	**.92**	
UB	.59 (.62)	.39 (.41)	.42 (.45)	.40 (.42)	.34 (.36)	.61 (.65)	.49 (.53)	.31 (.32)	.44 (.47)	.52 (.54)	.52 (.55)	.55 (.58)	**.94**

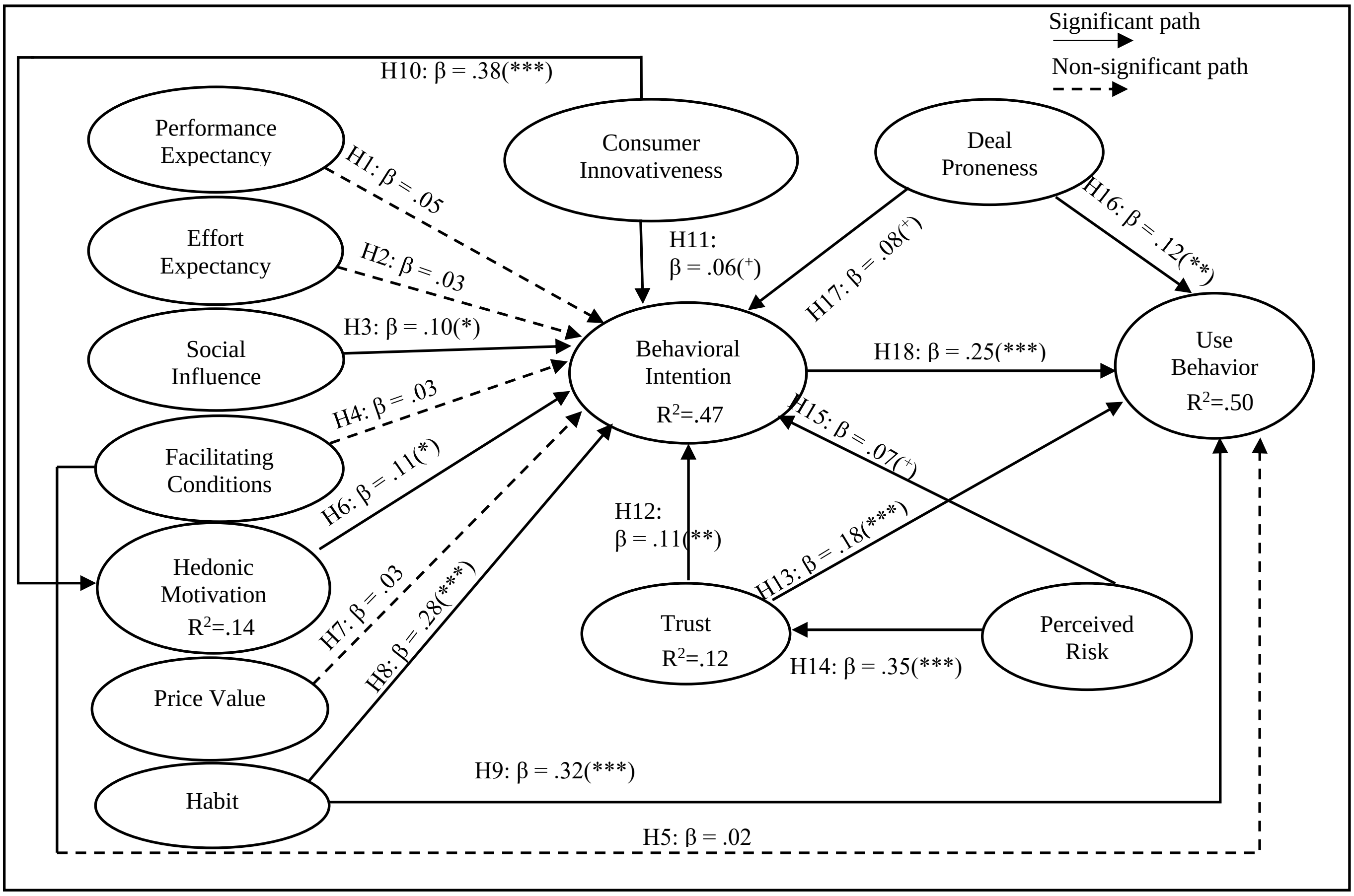
Note. Square root of AVE is presented in diagonal; value within bracket is the value of HTMT ratio; BI = behavioral intention, INT = consumer innovativeness, DP = deal proneness, EE = effort expectancy, FC = facilitating conditions, HA = habit, HM = hedonic motivation, PR = perceived risk, PV = price value, SI = social influence, TR = trust, UB = usage behavior.

Structural Model Analysis

PLS-SEM analysis was performed to assess H1 to H18. PLS algorithm with 300 iterations was used to test the statistics of the latent variables, and bootstrapping (5000 times) was applied to check the significance (Hair et al., 2019; Ringle et al., 2012). The root mean square residual covariance (RMS_{theta}) was applied to measure the model fit in the PLS-SEM (Lohmöller, 1989). The findings showed that the RMS_{theta} is .10, which is lower than a threshold value of .12; in other words, it indicates a well-fitting model (Henseler et al., 2014). In addition, the findings illustrated in Figure 2 indicate the relationship between the various constructs by analyzing the R^2, the Q^2, the significance of the path coefficient, and the effect size (f^2). First, the exogenous variables on behavioral intention, usage behavior, hedonic motivation, and trust are examined. The results indicate the model has a medium capacity to explain behavioral intention (R^2 = .47) and usage behavior (R^2 = .50), along with a weak explanatory power to hedonic motivation (R^2 = .14) and trust (R^2 = .12). Next, the predictive power of the model was measured by Q^2, and the results present predictive accuracy at a medium level for behavioral intention (Q^2 = .40), a nearly large level for usage behavior (Q^2 = .44), and at a small level for both hedonic motivation (Q^2 = .12) and trust (Q^2 = .10). Lastly, regarding the findings, it can be deduced that the main predictors of behavioral intention, in order of significance are: habit (β = .28, p < .00; f^2 = .08), trust (β = .11, p = .01; f^2 = .01), hedonic motivation (β = .11, p = .02; f^2 = .01), social influence (β = .10, p = .02; f^2 = .01), deal proneness (β = .08, p = .05; f^2 = .01), perceived risk (β = .07, p = .05; f^2 = .01), and consumer innovativeness (β = .06, p = .08; f^2 = .01). The major predictors of usage behavior, in order of importance are: habit (β = .32, p < .001; f^2 = .11), behavioral intention (β = .25, p < .001; f^2 = .07), trust (β = .18, p < .001; f^2 = .04), and deal proneness (β = .12, p = .00; f^2 = .02). In addition to the main endogenous variables, consumer innovativeness significantly impacts hedonic motivation (β = .38, p < .001; f^2 = .16); and perceived risk has significant effect on trust (β = .35, p < .001; f^2 = .14).

Figure 2

The Results of the Structural Model



Note. +p < .1, *p < .05, **p < .01, ***p < .001

Mediating and Moderating Effects

To more thoroughly examine the mediating impact between components in the theoretical framework, the mediating role of behavioral intention, hedonic motivation, and trust has been studied. After bootstrap estimation (5000 times), mediating effects were analyzed based on the regulation and steps applied by Zhou et al. (2021). That is, the mediating effects between constructs were examined through total effects, indirect effects, and direct effects. Firstly, the significance of total effects and indirect effects is a necessary condition for the meaningful existence of mediating effects. Furthermore, the mediator is viewed as a "partial mediator" if the direct effects are also significant; otherwise, it is regarded as a "full mediator." Table 5 illustrates behavioral intention has partial mediating effects on two paths; furthermore, hedonic motivation and trust have full mediating effects on their particular paths.

Table 5
Mediating Effects on the Structural Model Paths

Path	Effects	Estimate	Bootstrap 5000 Times			Percentile 95%		Conclusion
			S.E.	T-Statistics	P-Value	Low	Upper	
HA→BI→UB	Direct Effects	.32***	.04	7.10	.000	.23	.40	Partial Mediator
	Indirect Effects	.07***	.02	4.84	.000	.04	.10	
	Total Effects	.39***	.04	9.45	.000	.31	.47	
TR→BI→UB	Direct Effects	.18***	.04	4.29	.000	.10	.26	Partial Mediator
	Indirect Effects	.03*	.01	2.53	.011	.01	.05	
	Total Effects	.21***	.04	4.86	.000	.12	.29	
INT→HM→BI	Direct Effects	.06	.04	1.77	.077	-.01	.13	Full Mediator
	Indirect Effects	.04*	.02	2.36	.019	.01	.07	
	Total Effects	.10**	.04	2.63	.008	.03	.18	
PR→TR→BI	Direct Effects	.07	.04	1.94	.052	-.00	.14	Full Mediator
	Indirect Effects	.04*	.02	2.47	.013	.01	.07	
	Total Effects	.11**	.04	2.81	.005	.03	.18	

Note. *$p < .05$, **$p < .01$, ***$p < .001$; BI = behavioral intention, INT = consumer innovativeness, HA = habit, HM = hedonic motivation, PR = perceived risk, TR = trust, UB = usage behavior

Previous literature states that demographic variables have important moderating effects in various UTAUT models (Venkatesh et al., 2012). Thus, this study applied a multigroup analysis in a PLS path modeling framework (Sarstedt et al., 2011) to verify the moderating effects of age, gender, and experience on each path. According to this purpose, the samples in the two comparison groups were extracted as follows: gender, “male” and “female”; age, “born before 2000 (include 2000)” and “after 2000”, experience, “1-3 years and less” and “4-6 years and more”. Table 6 shows there are six significant moderating variables in the framework. Gender is the significant moderating variable on a path from consumer innovativeness to hedonic motivation (difference = -.24, p =.00) and from deal proneness to behavioral intention (difference = -.16, p = .04); age is the significant moderator on a path from facilitating condition to usage behavior (difference = .19, p = .01), and experience is the significant moderating variable on three paths: from facilitating condition to behavioral intention (difference = .21, p = .02) and usage behavior (difference = -.17, p = .02), and from habit to usage behavior (difference = .29, p = .00).

Table 6
Moderating Effects of Demographic Variables

	H4	H5	H9	H10	H17
	FC→BI	FC→UB	HA→UB	INT→HM	DP→BI
Gender					
Difference (Male - Female)	.15	.03	-.13	-.24	-.16
Diff. P-Value	.06	.65	.17	.00**	.04*
Age					
Difference (Before - After 2000)	.06	.19	.11	.00	.05
Diff. P-Value	.49	.01*	.24	.99	.57
Experience					
Difference (1 to 3 – 4 to 6 years)	.21	-.17	.29	.06	-.14
Diff. P-Value	.02*	.02*	.00**	.43	.12

Note. *p < .05, **p < .01, ***p < .001; BI = behavioral intention, INT = consumer innovativeness, DP = deal proneness, FC = facilitating conditions, HA = habit, HM = hedonic motivation, UB = usage behavior

Discussion and Conclusion

This study proposed a more comprehensive model in the context of live-streaming shopping to understand consumer intentions and behaviors in mainland China. PLS-SEM analysis on 860 valid responses revealed the relationship between the various constructs which are consistent with the theoretical assumptions of the current study.

According to the UTAUT2 mode presented by Venkatesh et al. (2012), the findings of this study indicated that social influence, hedonic motivation, and habit had a positive and significant effect on behavioral intention, which are in line with previous studies on online purchasing of tickets for low-cost carriers (Escobar-Rodríguez & Carvajal-Trujillo, 2014), mobile app based shopping (Tak & Panwar, 2017), live-streaming shopping (Zhou et al., 2021), hotel booking (Chang et al., 2019) and mobile banking usage (Çera et al., 2020). In addition, the result showed that habit is significantly and positively associated with consumer usage behavior of live-streaming shopping. It is in line with a study by Chopdar and Sivakumar (2019) on understanding Indian consumer continued usage of mobile-based shopping. More importantly, habit has been found as the strongest determinant of consumer intention in this study. It thus suggests that live-streaming vendors should execute marketing communication strategies that create the habit of using this new form of online shopping. For instance, live-streaming vendors often attract viewers through interactive chats in real-time and incentive rewards (Zhou et al., 2021). Using these incentives leads consumers to develop a habitual nature of using live-streaming shopping. Lastly, the result of this study was also strengthened by a majority of studies disclosing that the contribution made by behavioral intention positively and significantly impacted usage behavior (Çera et al., 2020; Escobar-Rodríguez & Carvajal-Trujillo, 2014).

This study comprised extra constructs as compliments to the UTAUT2 model. The consumer innovativeness was proved to have a significant and positive effect on hedonic motivation, which was consistent with a study by Droogenbroeck and Hove (2021) on Belgian consumer usage and adoption of E-grocery shopping. Besides, it’s positive and significant effect on behavioral intention was confirmed that is consistent with the research on Spaniards buying low-cost airline tickets online (Escobar-Rodríguez & Carvajal-Trujillo, 2014). More importantly, the study found a full mediating effect of hedonic motivation between consumer innovativeness and behavior intention. This result implies that persons with a high level of curiosity utilize live-streaming purchasing to fulfill their enjoyment. Live-streaming platforms combine pleasant social contact, the discovery of new products, outstanding promotions, expert reviews, and entertainment (Zhang et al., 2021).

Deal proneness and trust were included in this study to test the direct effects on behavioral intention and usage behavior. Likewise, perceived risk was also included to analyze the influence on trust and behavioral intention. The significant and positive relationship between these various constructs was in line with previous studies (Hong, 2015; Ling et al., 2011; Vakeel et al., 2018; Zhong et al., 2022). Furthermore, the study revealed that trust played the role of full mediator between the perceived risk to behavioral intention. That is, even if consumers are concerned about their privacy and security, they will still use live-streaming shopping when they meet more trustworthy vendors.

The effect of effort expectancy on behavioral intention was not significant in this study, which is in line with some previous studies (Çera et al., 2020; Chang et al. 2019; Mosquera et al., 2018). This may be due to the simultaneous development of smartphones and 5G Internet in China; it is not difficult for consumers to shop online anytime and anywhere. In addition, this study did not find significant effects of facilitating conditions on either behavioral intention or usage behavior of live-streaming shopping, which is consistent with a study by Zhou et al. (2021) on Chinese consumer intention to use live e-commerce shopping and a study of Çera et al. (2020) on mobile banking usage. This lack of empirical evidence may be because individuals use mobile phones with the internet in their daily lives; as a consequence, it should not be a hard task for them to shop through live-streaming platforms. Moreover, this study did not find a significant relationship between price value and behavioral intention, which is in line with several previous studies (Escobar-Rodríguez & Carvajal-Trujillo, 2014; Hanif et al., 2022; Mosquera et al., 2018; Zhou et al., 2021). It may be because the commodities offered on live-streaming platforms are chosen products, making it impossible for customers to discern pricing discrepancies. Lastly, contradicting prior studies (Zhou et al., 2021; Mosquera et al., 2018), this study did not provide empirical evidence of the performance effect on behavioral intention. It may be because the live-streaming vendors in China provide many products at the same period, so customers have to take time to wait for their targeted product. Therefore, the advantages of saving time and shopping efficiently are lacking.

This study examined the moderating effects of experience, age, and gender, which filled the gap of previous studies that have tested only the main effects or a subset of the moderating effects. The current study found that female users had a higher extent of innovativeness to impact their hedonic motivation than male users. Besides, female users were easier attracted by the provided promotion than male users. In addition, users who were born before 2000 had more facilitating conditions than users who were born after 2000; thus, they would have more chances to go shopping through a live-stream platform. Lastly, users with less live-streaming shopping expertise were more easily influenced by facilitating conditions than users with greater live-streaming shopping experience. Conversely, users with more live-streaming shopping experience were more easily impacted by facilitating conditions while they purchased through live-streaming platforms.

Limitations

The contributions of this study should be noted in light of some limitations. On one hand, a convenience sampling method was used to collect data, so there was an inability to generalize the results of the survey to the population as a whole. On the other hand, this study included only new exogenous variables for comprehending the model. Thus, for developing a more comprehensive model, a new outcome variable such as consumers desire to suggest new technology to others might be included in this model.

Implications for Behavioral Science

This study provides suggestions on predicting consumer intention and actual use of live-streaming shopping. On one hand, the strongest predictor of habit on behavioral intention indicates that merchants should consider live-streaming platforms for business-to-customer transactions, as the development of live streaming platforms has led consumers to use live streaming as a way to shop online. On the other hand, trust is the second strongest predictor of behavioral intention, which implies that the good quality of commodities, complete after-service, and the protection of consumer interests are conditions to improve consumer trust in live-streaming shopping, thereby taking a purchasing action.

Conclusion

The purpose of this study was to propose a more comprehensive model to understand Chinese consumer intention and usage behavior of live-streaming shopping. The data was gathered through a self-administered questionnaire in mainland China. The findings found significant and positive relations of social influence, hedonic motivation, habit, trust, perceived risk, and deal proneness on behavioral intention; habit, trust, deal proneness, and behavioral intention on usage behavior of live-streaming shopping; consumer innovativeness on hedonic motivation; and perceived risk on trust. Therefore, the study enhances the existing knowledge of the UTAUT2 framework in the context of e-commerce. In addition, the findings also provide important behavioral implications for assisting to characterize the consumer intention and usage behavior towards applying live-streaming shopping.

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