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Social media influencer streamers and live-streaming shopping: examining consumer behavioral intention through the lens of the theory of planned behavior

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Abstract

The rapid development of live streaming has given rise to live-streaming shopping, a novel channel of online shopping that has gained considerable market value. While previous studies have explored various factors influencing consumers' intentions to engage in live-streaming shopping, most have focused on factors influencing behavioral intention after consumers have already chosen live-streaming as their online shopping channel. Few studies have focused on the beginning of the entire shopping journey—the intention of consumers to choose live-streaming shopping. To fill this research gap, this study extends the theory of planned behavior by introducing social media influencer streamers as an exogenous variable. We investigated how attitudes toward live-streaming shopping, subjective norms, perceived behavioral control, and social media influencer streamers collectively influence the consumer's intention for live-streaming shopping. To achieve those research objectives, the study distributed an online questionnaire across four specific regions in the Chinese market. By using stratified sampling and purposive sampling methods, we garnered 385 valid responses from those four regions. The study employed partial least squares structural equation modelling and SmartPLS 4.0 for data analysis. Consequently, the results show that both attitudes toward live-streaming shopping, subjective norms, perceived behavioral control, and social media influencer streamers have a significant on consumers' intention for live-streaming shopping. Moreover, social media influencer streamers exhibit significant influences on consumers' attitudes toward live-streaming shopping, subjective norms, and perceived behavioral control.

Keywords Social media influencer streamers, Live streaming, Live-streaming shopping, Intention, Theory of planned behavior

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Introduction

With the advancement of internet technology and the widespread use of mobile smartphones, there has undergone a significant transformation in the way people communicate. Notably, the advent of social media has shifted the traditional one-way communication model to a bidirectional interactive model [49]. Enke and Borchers [38] asserted that individuals are no longer merely consumers of content on social media platforms, they also act as content producers. Applications such as TikTok, Instagram, Twitter, and Facebook have gradually become crucial channels for information retrieval and sharing [9]. In this context, Onofrei et al. [83] pointed out that interpersonal interactions have become more frequent and intimate, fostering deeper connections among users. These enhanced user relationships subtly influence consumer consumption behaviors. Particularly in the realm of online shopping, Shiu et al. [92] indicated that interpersonal relationships affect consumers' choice of online channels. Concurrently, enterprises are leveraging the profound connections established on social media to conduct online marketing activities, achieving desired market effects. Among these, live-streaming shopping has become a popular trend in the online shopping industry.

In recent years, continuous advancements in live-stream technology have elevated its significance in people's daily lives. Particularly in China, platforms such as Douyin, Kuaishou, Taobao, and Xiaohongshu have integrated live-streaming functions into entertainment, education, gaming, and e-commerce, significantly impacting the lifestyles of Chinese users [74, 89, 106]. According to the China Internet Network Information Center (CNNIC), the number of live-streaming users in China reached 750.65 million in 2022, more than doubling since 2016 [33]. Moreover, the penetration rate of live-streaming in online activities among netizens increased by 23%, reaching 70.3% [33]. Given the extensive user base and high penetration rate, enterprises have keenly recognized the potential market value brought by live streaming. Increasingly, businesses are frequently utilizing live-stream functions on social media for product sales [76]. For instance, during Alibaba's Double Eleven pre-sale event on Taobao Live in 2020, the total transaction amount reached an impressive $7.5 billion within the first 30 min [10]. Similarly, a survey by AlixPartners [6] revealed that over two-thirds of Chinese consumers expressed an intention to shop via live-stream during the Double Eleven event in 2020. According to Statista [93], the gross merchandise value of China's live-streaming economy reached 3500 billion RMB in 2022, a rapid growth compared to 19.64 billion RMB in 2017. To some extent, live-streaming has become a new business model driving the development of online shopping in China [79].

However, despite these impressive achievements, there are still controversial issues, with the most significant being the persistently high return rates. According to 36KRResearch [1], the return rate for live-streaming commerce in China reached 30–50% in 2020, significantly higher than the 10–15% return rate for traditional online shopping. The rising return rate indicates higher post-purchase costs for consumers in live-streaming commerce. Similarly, the China Consumers Association (CCA) reported that the main reasons consumers are reluctant to try live-streaming shopping are concerns about quality assurance and potential after-sales issues, accounting for 60.5% and 44.8%, respectively [24]. These figures suggest that many factors still influence consumers' live-streaming shopping behavior, posing significant barriers to the development of live-streaming commerce.

To address this issue, many scholars have attempted to study consumers' live-streaming shopping behavior from various perspectives. Generally, Mai et al. [79] categorized related live-streaming shopping research into three types: streamer-related research, consumer-related research, and platform-related research. Specifically, Gao et al. [41] pointed out that since streamers dominate the whole live-streaming activities, streamer-related factors, such as characteristics [44, 109], significantly impact consumer behavior. In terms of consumers, how they engage [103, 107] and how they feel [12, 101] also significantly influence their performance in live-streaming shopping. Additionally, different platform features and functionalities affect consumers' live-streaming shopping experiences, subsequently influencing their purchasing behaviors [45].

However, it is worth noting that these empirical studies were primarily conducted after consumers had already chosen live-streaming as their preferred online shopping channel. The initial stage of the live-streaming shopping journey, specifically the motivations behind consumers choosing live-streaming shopping over traditional online shopping channels, remains unexplored. This research gap is particularly relevant given the high return rates in the Chinese live-streaming market compared to traditional online shopping, yet live-streaming shopping remains popular among Chinese consumers. Meanwhile, top-tier streamers, such as social media influencer streamers, not only have the capability to attract a larger consumer base but also maintain a notably low return rate of 10–15% [54].

Therefore, this research aims to fill the existing research gap by exploring the factors influencing consumers' intention to choose live-streaming shopping. To this end, we employed the Theory of Planned Behavior (TPB) to investigate consumer behavioral intention. According to TPB, consumers' attitudes toward behavior, subjective norms, and perceived behavioral control are three critical factors influencing whether consumers perform a behavior. Additionally, due to the dual attributes of live-streaming shopping, we argue that social media influencer streamers also play a crucial role in influencing consumers' decisions. Thus, we propose incorporating social media influencer streamers as a new factor in the TPB mode, hypothesizing that social media influencer streamers, alongside the original three factors, influence consumers' behavioral intention. Furthermore, we suggest that social media influencer streamers impact consumers' attitudes toward live-streaming shopping, subjective norms, and perceived behavioral control. As a result, this research extends the TPB model by introducing a new variable, enhancing its applicability in the context of live-streaming shopping. Additionally, this research focuses on consumers' intention to choose live-streaming, contributing to the existing research on consumer behavior in the live-streaming shopping domain.

Literature review

Live-streaming shopping

Live-streaming shopping enables consumers to shop while watching live streams. This provides a novel online shopping experience and marketing channel for both consumers and businesses.

Previous research has extensively compared live-streaming shopping with traditional online shopping, highlighting significant differences. Unlike traditional online shopping, Chen et al. [29] noted that live-streaming shopping combines the dual attributes of social media and e-commerce, providing consumers with a unique and engaging online shopping experience. On one hand, streamers (sellers) actively promote and introduce products during live broadcasts, while viewers (consumers) make purchases as they engage with the live content. In this dynamic transaction process, consumers interact with real people rather than static shopping web pages [7, 106]. Chang and Yu [26] suggested that by communicating with streamers or other viewers, consumers immerse themselves in an interactive online shopping scenario. This socially driven shopping method more effectively meets consumer consumption needs and facilitates transaction completion [92]. On the other hand, by utilizing live video technology, merchants can vividly demonstrate products, allowing consumers to evaluate products more thoroughly [50]. This form of product demonstration, which relies on live demonstrations rather than static images and text, provides consumers with richer and more valuable information [84, 89]. As Gao et al. [42] emphasized, the information consumers gather during online shopping significantly influences their product evaluation and purchase decisions, especially when they cannot physically touch the products. From this perspective, live-streaming shopping enhances the effectiveness of product information transmission compared to traditional online shopping.

Additionally, the combination of live-streaming shopping with social media influencers has emerged as a powerful marketing strategy. Barta et al. [13] noted that social media influencers, by offering content that resonates with consumers, more effectively represent their followers' interests, lifestyles, and values compared to traditional celebrities. Therefore, Ki and Kim [58] argued that social media influencers can establish deeper bonds with their followers. These bonds make influencer endorsements appear more authentic and trustworthy [73] compared to traditional marketing methods [20]. Thus, the combination of live-streaming shopping and social media influencers leverages the interactivity of live-streaming and the influence of influencers' personalities, significantly enhancing brand exposure and consumer purchase intentions.

In this study, we introduce the term "Social Media Influencer Streamers" (SMISs), referring to social media influencers who act as live streamers, promoting products in real-time during their broadcasts.

The theory of planned behavior

The theory of planned behavior (TPB), developed by Icek Ajzen in 1985, aims to elucidate and predict individual behavioral intentions [4]. This theoretical model is considered an extension of the earlier Theory of Reasoned Action (TRA) [21]. The TRA model assumes that individuals have complete control over their behavior, a premise that does not apply to actions influenced by external factors or lacking full volitional control. To address the limitations of the TRA, Ajzen [5] introduced the concept of perceived behavioral control to measure individuals' control beliefs, thereby providing a more comprehensive framework. Consequently, the TPB posits that individual behavior is determined by three key factors: attitudes toward the behavior, subjective norms, and perceived behavioral control [4]. Since its inception, the TPB model has been widely applied across various research domains as an effective model for predicting and explaining individual behavior [11, 14, 80, 104].

According to TPB, an individual's attitude towards a particular behavior is pivotal in shaping their behavioral intentions [7, 102]. Broadly, attitude is defined as an individual's overall evaluation of the behavior and its potential outcomes [5]. Similarly, Armitage and Conner [8] used the concept of behavioral belief to describe individuals' attitudes toward behavior, noting that these are influenced by the subjective value attached to the expected outcomes of the behavior. Essentially, as emphasized by Stranieri et al. [94], individuals' attitudes toward a behavior are shaped by evaluations of the associated outcomes, whether perceived as positive, negative, or neutral. For example, in the contexts of health behaviors [94, 104], environmental behaviors [78, 86], and marketing behaviors [35, 108], individuals are more likely to engage in behaviors they perceive as beneficial. Generally, as noted by Masukujjaman et al. [80], a positive attitude towards behavior is a strong predictor of an individual's intention to engage in a particular behavior.

While an individual's attitude towards a behavior is crucial, the environment in which they act also significantly shapes their actions and decisions. In this sense, Ajzen [5] underscored the importance of subjective norms as a key determinant of individual behavior. Subjective norms involve an individual's perception of external pressures from others, which may influence their decision to engage in or avoid specific behaviors [5, 52]. Specifically, Zhou and Liu [108] highlighted that the tendency to conform to expectations related to a certain behavior is influenced by subjective norms, including normative views within the social environment. In other words, as Joo et al. [56] asserted, an individual's behavioral intentions are easily swayed by the opinions of third parties, such as friends, family, and other significant persons. Thus, Aydin and Aydin [11] pointed out that subjective norms underscore the impact of the social environment on individual behavior.

Additionally, Rohde [88] emphasized that perceived behavioral control reflects an individual's confidence in their ability to perform a specific behavior. However, Huang et al. [52] noted that perceived control over behaviors may vary across different contexts and behaviors. Similarly, Ajzen [5] acknowledged that individuals' reflections on perceived behavioral control may differ based on their past experiences, skills, resources, and situational constraints. In this regard, Rohde [88] suggested that perceived capability and perceived controllability are the most effective indicators for assessing perceived behavioral control. Perceived capability pertains to the perceived ease or difficulty of performing a particular behavior, while perceived controllability refers to the sense of control over executing the behavior [14, 88]. In other words, D'Souza et al. [35] argued that beliefs about one's ability to control a behavior in a given context significantly influence the propensity to engage in that behavior. Similarly, this notion aligns with Aydin and Aydin [11], those who claimed that the likelihood of engaging in a specific behavior increases in tandem with the sense of control over that behavior.

However, as market environments continuously evolve, the factors influencing individual behavioral intentions have become more complex, revealing the limitations of the traditional TPB. Scholars have begun to expand the TPB model [21, 77]. For instance, Valentin and Hechanova [96] introduced perceived quality and self-identity as variables to further predict individual behavioral intentions from the perspectives of product and personal value. Similarly, Magrizos et al. [77] demonstrated that product price and self-identity significantly influence consumer purchase intentions. Additionally, Wang et al. [98] validated the applicability of consumer familiarity and ambiguity tolerance within the TPB model. The rise of social media and live streaming has further diversified the factors affecting consumer purchase intentions. For example, Chetioui et al. [30] and Chopra et al. [32] introduced influencer-related variables, proving their significant impact on consumer purchase intentions. Likewise, Huang et al. [52] emphasized the influence of social distance on the behavioral intentions of online users.

Therefore, to accurately predict consumer behavioral intentions in the live-streaming market, it is imperative to extend the original TPB model.

Hypotheses development

Attitudes toward live-streaming shopping

The advantages offered by online shopping have made it the preferred shopping channel for many consumers [15, 89]. This consumption behavior is significantly influenced by consumers' positive perceptions. Erkan and Elwalda [39] pointed out that consumers can access information from various sources during online shopping, aiding them in better evaluating product value. This information accessibility facilitates more informed purchasing decisions, fostering a positive attitude towards online shopping. Additionally, Patel et al. [85] emphasized that online shopping provides consumers with reliable customer reviews, enhancing consumer trust. When consumers trust online shopping, they are more likely to engage in it [87, 97].

As an innovative approach to online shopping, live-streaming shopping offers greater value compared to traditional online shopping channels. For instance, Chen et al. [28] and Liu et al. [71] proposed that live-streaming shopping not only provides consumers with more cost-effective products but also meets their social needs. Similarly, Chen et al. [29] highlighted that live-streaming shopping enables real-time communications among consumers, streamers, and other viewers, fostering closer social connections. This social engagement not only enhances the enjoyment of the shopping experience but also boosts consumer confidence and decisiveness in their purchasing decisions [29, 68].

Moreover, De Cannière et al. [36] noted that consumers' attitudes toward behaviors are closely related to their past experiences. This implies that satisfaction derived from past experiences strengthens their attitudes, thereby increasing their intention to engage in the behavior. Therefore, when consumers hold a positive attitude towards online shopping, they are more likely to choose live-streaming shopping, a more valuable online shopping channel, when deciding on an online shopping method. Consequently, we propose the following hypothesis.

H1: The consumer's attitudes toward live-streaming shopping have a significant impact on the consumer's intention for live-streaming shopping.

Subjective norms

The influence of subjective norms on consumer behavioral intentions is particularly evident in the context of online shopping. For instance, Bhatti and Akram [19] noted that consumers, especially during their first online shopping purchase, tend to heavily rely on the opinions of others when deciding whether to make purchases. Similarly, Theodorou et al. [95] observed that the attitudes within a consumer's social circle significantly impact their online shopping decisions. Additionally, Sajid et al. [90] emphasized the substantial influence of norms formed through interpersonal interactions on consumers' online shopping behavior. Specifically, consumers often reference other users' reviews and ratings when shopping online, which subsequently influences their purchasing decisions [64, 91]. In other words, the opinions and attitudes of others are critical factors affecting consumer decisions in online shopping.

In the case of live-streaming shopping, interpersonal interaction is more frequent compared to traditional online shopping channels [7, 63]. This increased interaction means that consumers can receive more opinions, recommendations, and reviews from others during the live-streaming shopping [50]. These valuable inputs ultimately influence consumer behavioral intentions [29]. On the other hand, Lin et al. [70] noted that as live streaming gradually integrates into consumers' daily lives, live-streaming shopping is becoming a new trend in online shopping. When consumers see friends, family, or influencers participating in live-streaming shopping, it creates a normative expectation that this behavior is acceptable and desirable.

Therefore, we propose that for live-streaming shopping, as a highly social online shopping channel, subjective norms play a crucial role in shaping consumer behavioral intentions.

H2: Subjective norms can positively influence the consumer's intention for live-streaming shopping.

Perceived behavioral control

The positive relationship between perceived behavioral control and behavioral intention in the context of online shopping has been well established [67, 85]. As Petcharat and Leelasantitham [87] pointed out, online shopping offers consumers unparalleled convenience by eliminating the need for physical presence in stores. This convenience allows consumers to complete shopping activities anytime and anywhere, leveraging the flexibility and accessibility provided by digital platforms. In other words, Gong et al. [43] noted that consumers have the ability to control the entire online shopping process and decide whether to engage in online shopping behaviors. This implies that consumers have the autonomy to manipulate their online shopping experience.

Moreover, in live-streaming shopping, consumers have more freedom to control their choices and behaviors. Cai et al. [22] pointed out that consumers can select which live-stream content to watch based on their interests, needs, and preferences. This autonomy allows consumers to explore various products, make comparisons, and ultimately make purchasing decisions [22, 102]. If consumers find that live-stream content uninteresting or irrelevant to their needs, they have the autonomy to stop watching, thereby preventing any purchase behavior [99, 100]. Therefore, we propose the following hypothesis:

H3: Perceived behavioral control significantly influences the consumer's intention for live-streaming shopping.

Social media influencer streamers

Previous studies have consistently shown that collaboration with social media influencers can be an effective marketing strategy, particularly in the domain of social commerce [13, 58, 73]. As Lou and Yuan [73] noted, by partnering with social media influencers, brands can reach a vast and engaged follower base, enabling them to connect with potential customers in a more targeted and authentic manner. Additionally, investigations into the impact of social media influencers on consumer behavior suggest that their effectiveness stems from the deep reciprocal relationships they establish with consumers [23, 59, 72]. Through these relationships, Kim and Kim [59] argued that the psychological distance between consumers and social media influencers is reduced, making consumers more susceptible to the influencers' recommendations and endorsements.

As social media influencers transition into live-streaming as streamers for product sales, their influence seamlessly extends from social platforms into live-streaming shopping. It means that this continuity in SMISs' influence and presence may lead their followers to perceive these activities as trustworthy and reliable. Therefore, we posit the following hypothesis:

H4: Social Media Influencer Streamers have a positive impact on the consumer's intention for live-streaming shopping.

Furthermore, SMISs can significantly influence consumers' attitudes toward live-streaming shopping. As previously mentioned, consumers' attitudes towards a behavior are contingent upon their evaluation of the outcomes associated with that behavior. Enke and Borchers [38] highlighted that due to the sincere interactions social media influencers have with consumers on social media platforms, they positively impact consumers' psychological states, leading to a heightened sense of trust in social media influencers. Based on this trust, Kim and Kim [59] emphasized that consumers are more inclined to accept social media influencers' opinions. In other words, consumers often believe that influencers can bring beneficial content to them [17].

In the online shopping environment, this reliance on influencers becomes even more critical. Although information technology enables consumers to access extensive product-related information to make informed online purchasing decisions [23], Zatwarnicka-Madura et al. [105] pointed out that the unrestricted nature of online information sharing also presents challenges in discerning accurate and reliable information. In this context, Beheshti et al. [16] suggested that social media influencers who are perceived as authoritative and trustworthy in specific domains can alleviate the challenge of obtaining valuable information to some extent. Therefore, as highlighted by Hu et al. [51], consumers are more likely to form positive impressions of social media influencers, due to their ability to provide trustworthy and valuable information. Additionally, Apasrawirote and Yawised [7] highlighted that in the context of online shopping behavior, influencers can significantly influence consumers' attitudes, thereby impacting their behavioral intentions toward products endorsed by influencers. Consequently, Magrizos et al. [77] concluded that consumers' attitudes toward social media influencers play a crucial role in determining whether they engage in behaviors associated with social media influencers.

Therefore, we posit that in live-streaming shopping, SMISs can influence consumers' attitudes towards live-streaming shopping behavior, and we propose the following hypothesis:

H5: Social Media Influencer Streamers have a positive impact on the consumer's attitudes toward live-streaming shopping.

Moreover, social media influencers exert a significant impact not only on consumers but also on broader social networks [21, 32]. As described by Magrizos et al. [77], the fan effect illustrates how social media influencers develop profound relationships with their followers, leading to supportive and endorsing behaviors among fans. Furthermore, Borchers [20] noted that once consumers become followers of influencers, they may even persuade others to engage in activities associated with these influencers. Particularly, peer recommendations originating from these followers are perceived as sincere and devoid of commercial motives, thus possessing substantial persuasive power, as emphasized by De Jans et al. [37]. Consequently, to some extent, the influence of social media influencers on consumer behavior extends to others through the endorsements of their followers.

In the context of live streaming, the real-time nature of content transmission enhances the frequency and significance of interactions between streamers and viewers [65]. In such scenarios, the interwoven relationships among social media influencers, followers, and other viewers facilitate the rapid dissemination of opinions and behaviors within the community [99, 100]. As Shiu et al. [92] pointed out, this communal atmosphere fosters a sense of belonging and loyalty among viewers, thereby contributing to the spontaneous formation of influence and behavioral norms. Additionally, as discussed by Lin et al. [69], the concept of social media influencers as micro-celebrities implies that consumer behavior can be influenced by imitating the actions and choices of influencers [2, 3]. According to Jin and Ryu [55], this phenomenon of social mimicry suggests that consumers may replicate the behaviors endorsed or demonstrated by social media influencers. From this perspective, when consumers observe social media influencers endorsing specific behaviors, they may perceive these behaviors as normal or socially acceptable [55]. Consequently, SMISs' behaviors could contribute to the establishment of social norms within online shopping and broader society. In light of these insights, we propose the following hypothesis:

H6: Social Media Influencer Streamers have a positive impact on subjective norms.

Furthermore, in the context of live-streaming shopping, SMISs possess unique purchasing influence. According to iresearch [54], top-tier streamers often hold monopolistic bargaining power. It means that these streamers have a dominant position when negotiating prices with suppliers, enabling them to offer relatively more favorable prices to consumers compared to other shopping channels. As emphasized by Cheah et al. [27], price has consistently been the most critical factor influencing consumer shopping behavior. Given equal conditions, consumers are more likely to purchase products or services that are priced lower. A survey conducted by CCA [24] revealed that 53.9% and 43.8% of users cited discount prices and limited-time offers, respectively, as reasons for participating in live-streaming shopping. Therefore, the price advantages brought by SMISs influence consumers' consideration of resource investment in online shopping behavior, subsequently affecting their choice of online shopping channels.

Moreover, as previously discussed, consumers in live-streaming shopping do not complete the entire shopping process in isolation. Instead, consumers autonomously immerse themselves in the entire live-streaming process [22], assessing the value of products by watching SMISs' demonstrations and interacting with other users before ultimately deciding whether to make a purchase. During this process, as Ingard [53] noted, the streamer controls the entire live session, systematically showcasing, explaining, and selling products to consumers. The content consumers see during the stream is determined by the streamer [28]. Additionally, streamers selectively engage with users and guide their participation behaviors, such as liking, sharing, and commenting. To a certain extent, streamers can influence how consumers act in live streaming.

Therefore, we propose the following hypothesis:

H7: Social Media Influencer Streamers have a positive impact on perceived behavior control.

Research framework

Based on the preceding discussion, the proposed research framework is illustrated in Fig. 1. In total, seven hypotheses are formulated to be validated.

Methodology

Sample size determination

To ensure our collected sample data effectively reflects our research objectives and provides statistically meaningful results, the determination and selection of samples become crucial. Previous studies have offered various methods for determining an appropriate sample size, such as sample size calculation formulas or specialized software tools [57, 62]. Among these, when dealing with a large population in research, Lakens [62] suggested that sample size calculation formulas stand out as an efficient and convenient means of determining sample size.

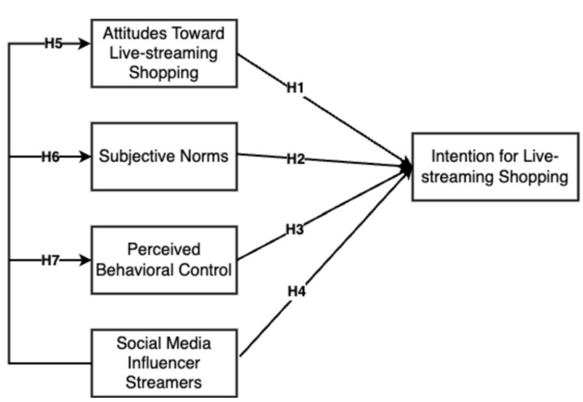

Fig. 1 Research framework

Given that the focus of this study is to explore the behavioral intent of Chinese consumers in choosing live-streaming shopping during online shopping, the population under investigation comprises all online shopping consumers in the Chinese market. According to CNNIC [33], the number of online shopping consumers in China reached 8.45 billion in 2022. Consequently, to extract a suitable sample size from such a vast population, we employed Cochran's formula [34], which is particularly well-suited for studies with large populations. The formula is as follows:

$$n = \frac{Z^2 \times p \times (1-p)}{E^2}$$

where

n = The required sample size.

Z = Chosen level of significance (typically for a 95% confidence level, Z would be about 1.96).

p = Estimated population proportion (anticipated sample proportion, a value between 0 and 1).

E = Margin of error (allowable error between the sample proportion and the population proportion).

To ensure the credibility of the obtained sample, we set the confidence level at 95% and the margin of error at 5%, corresponding to Z = 1.96 and E = 0.05, respectively. Additionally, considering the rapid growth of live-streaming shopping in China, which has become a popular online shopping method for consumers, we reasonably assumed that approximately half of the 8.45 billion online shopping consumers engage in live-streaming shopping. It means that the value for p is 0.5. Substituting these values into the calculation formula, we derived the following expression:

$$n = \frac{1.96^2 \times 0.5 \times (1-0.5)}{(0.05)^2} = \frac{0.9604}{0.0025} = 384.16 \approx 385$$

Since n must be a whole number, we round up to the nearest whole number. Therefore, the calculated sample size required for our study is 385.

Sample size composition

As China's vast size and diverse regional economies can lead to significant variations in consumer preferences, behaviors, and purchasing patterns across different regions. Thus, we categorized the sample based on regional divisions to ensure the representativeness of the sample. According to the National Bureau of Statistics of China (NBSC), China can be categorized into four areas based on socio-economic development: Eastern, Central, Western, and Northeastern areas [82]. Subsequently,

Table 1 Sample composition

Areas	Regions	Online retail sales value (100 million yuan)	Population (million)	Sampling proportions (%)	Sample size
Eastern area	Guangdong	28,467.2	126.84	36.1	139
Central area	Henan	2948.2	98.83	28.1	108
Western area	Sichuan	3889.1	83.72	23.8	92
Northeastern area	Liaoning	1654.1	42.29	12	46
Total	4	36,958.6	351.68	100	385

Source: [82]

according to NBSC [82], we selected the region with the highest online retail sales in each of these four areas in 2021 as the source region for the sample. To do so, we utilized stratified sampling to determine the sample sizes for each region. First, we calculated the sampling proportions for each stratum by dividing the total population of each region by the total population of all four regions. Then, we multiplied the sample size of 385 by each stratum's sampling proportion to obtain the number of samples to be taken from that stratum. Table 1 outlines the specific details of the sample composition.

Data collection

Due to the diverse geographical origins of our samples across four regions in China, we employed an online questionnaire as it is a practical and efficient approach for data collection [61]. To maximize participant outreach, we selected the widely used online survey platform, Wenjuanxing, known for its substantial market presence in China. To minimize external influences on respondents, we utilized a self-administered structured questionnaire, accessible via web browsers or mobile devices.

Furthermore, we opted for a purposive sampling method to ensure that our participant pool is targeted and representative of specific characteristics relevant to our research objectives. As described by Berndt [18] and Kim [60], purposive sampling involves selecting participants based on predefined criteria that align with the aims and scope of the study. To do so, two screening questions were introduced at the beginning of the questionnaire, assessing participants' recent experiences in online shopping and live-streaming shopping within the past month. Only respondents affirming both experiences proceeded to complete the questionnaire. Finally, we collected responses from 423 participants. Following a meticulous exclusion process, including scrutiny of screening questions, logical consistency, and response times, we identified and retained 385 valid responses for subsequent data analysis.

Table 2 Demographic information

Variable	Categories	Frequency	Percentage
Gender	Male	164	42.6
	Female	221	57.4
	Total	385	100
Age	18–28	194	50.3
	29–43	167	43.4
	44–59	13	3.4
	Above 60	11	2.9
	Total	385	100
Education	Senior high school or below	13	3.3
	Bachelor's or associate degree	252	65.5
	Master's degree	114	29.6
	PhD	6	1.6
	Total	385	100
Frequency of watching live streaming	Multiple times a day	84	21.8
	Everyday	142	36.9
	3–4 days per week	131	34
	Very rare	28	7.3
	Total	385	100

Demographic profile

Table 2 shows the complete demographic information for the 385 respondents. Of these, 164 are male, while 221 are female. The majority of respondents belong to the Generation Z and Generation Y categories, with a significant portion indicating a high frequency of live-streaming viewership.

Measurement items

To ensure the fidelity of the questionnaire's meaning during translation, it was initially drafted in English and subsequently translated into Mandarin. In our study, to impartially capture respondents' authentic opinions on the measurement items, we employed a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly

Table 3 Measurement items

Constructs	Items	Resources
Attitudes Toward Live-streaming Shopping (ATT)	ATT1. I like the idea of purchasing products from live streaming	Patel et al. [85]
	ATT2. The idea of using live streaming to purchase products is appealing	
	ATT3. My attitude towards live-streaming shopping is positive	
Subjective Norms (SN)	SN1. People who matter to me think that I should buy products from live streaming	Patel et al. [85]
	SN2. I feel social pressure to purchase products from live streaming	
	SN3. I think I should purchase products from live streaming as people around me do the same	
Perceived Behavioral Control (PBC)	PBC1. I feel like I have control over my decision to purchase products from live streaming	Patel et al. [85]
	PBC2. I have enough money to purchase products from live streaming	
	PBC3. It is easy for me to purchase products from live streaming	
Social Media Influencer Streamers (SMIS)	SMIS1. I think social media influencer streamer can assist me in making shopping decisions	Chetioui et al. [30]
	SMIS2. I believe that social media influencer streamer provides valuable products to me	
	SMIS3. I believe that social media influencer streamer provides new deals about different products	
Intention for Live-streaming shopping (ILSS)	ILSS1. I would consider purchasing products from live streaming	Lu and Chen [75]
	ILSS2. I am inclined to purchase products from live streaming in the future	
	ILSS3. I am very likely to purchase products from live streaming	

agree). All measurement items adopted and adapted were derived from previously established research. The questionnaire assesses five distinct factors: attitudes toward live-streaming shopping (ATT), subjective norms (SN), perceived behavioral control (PBC), social media influencer streamer (SMIS), and intention for live-streaming shopping (ILSS) (refer to Table 3). Each latent variable comprises three indicators. Table 3 presents all constructs, measurement items, and resources.

Statistical methods

This study used a variety of statistical techniques for data analysis. For example, descriptive statistical methods were utilized during the data-cleaning stage to summarize and describe the main features of the data. Additionally, Partial Least Squares Structural Equation Modeling (PLS-SEM) was applied to evaluate the proposed model and test hypotheses. Path analysis was conducted to examine the relationships between variables. All data analyses were performed using SmartPLS 4.0 software.

Results

Descriptive statistics and multicollinearity

Before delving into more in-depth data analysis, we employed statistical methods such as calculating the mean and standard deviation to gain insights into the distribution and characteristics of our data. The descriptive data obtained is presented in Table 4. These preliminary

Table 4 Descriptive statistics and multicollinearity

Model	Items	Mean	Standard deviation	VIF
Outer model	ATT1	4.174	0.873	1.464
	ATT2	3.995	0.742	1.557
	ATT3	4.379	0.921	1.533
	SN1	4.309	0.892	1.566
	SN2	4.197	0.881	1.527
	SN3	4.016	0.776	1.531
	PBC1	4.000	0.844	1.719
	PBC2	4.174	0.987	1.431
	PBC3	3.971	0.804	1.574
	SMIS1	4.270	0.840	1.407
	SMIS2	3.961	0.770	1.442
	SMIS3	4.273	0.921	1.480
	ILSS1	4.226	0.792	1.908
	ILSS2	4.340	0.829	1.990
	ILSS3	4.296	0.760	1.702
Inner model	ATT -> ILSS	–	–	2.993
	SN -> ILSS	–	–	2.985
	PBC -> ILSS	–	–	2.654
	SMIS -> LSS	–	–	2.952
	SMIS -> ATT	–	–	1.000
	SMIS -> SN	–	–	1.000
	SMIS -> PBC	–	–	1.000

Table 5 Factor loadings, Cronbach's alpha, composite reliability, and AVE

Constructs	Items	Loadings	Cronbach's alpha	Composite reliability	AVE
Attitudes toward live-streaming shopping	ATT1	0.818	0.754	0.859	0.670
	ATT2	0.816			
	ATT3	0.821			
Subjective norms	SN1	0.841	0.762	0.863	0.677
	SN2	0.819			
	SN3	0.808			
Perceived behavior control	PBC1	0.857	0.761	0.863	0.677
	PBC2	0.792			
	PBC3	0.819			
Social media influencer streamer	SMIS1	0.790	0.730	0.848	0.650
	SMIS2	0.820			
	SMIS3	0.807			
Intention for live-streaming shopping	ILSS1	0.875	0.822	0.894	0.737
	ILSS2	0.876			
	ILSS3	0.823			

analyses help us understand the central tendency and variability of our variables, laying a solid foundation for more in-depth exploration and interpretation of the data. Concurrently, we conducted multicollinearity tests to ensure the absence of high correlation among the data, which is essential for multiple regression analysis.

Initially, we assessed the collinearity between each indicator, with the highest collinearity observed between ILSS1 and ILSS2, at 0.653. This value is well below the recommended threshold of 0.75 [46], indicating no collinearity between indicators. Subsequently, to further validate multicollinearity, we performed variance inflation factor (VIF) calculations for both the outer and inner models. All variable VIF values were below the widely accepted threshold of 5, signifying the absence of multicollinearity [48]. Additionally, the inner model's VIF values indicated that our model can be considered free of common method bias. The results are detailed in Table 4.

Measurement model assessment

Since this study employs PLS-SEM for data analysis, we followed the recommended steps outlined by Hair et al. [46] for PLS-SEM data analysis. The initial step involved assessing the measurement model. This phase is crucial as it ensures the reliability and validity of the measurement instruments used in the study [25, 48]. To do so, we conducted reliability analyses. During this process, Cronbach's alpha, composite reliability, and average variance extracted (AVE) were examined. The results indicate that Cronbach's alpha and composite reliability values for all latent variables exceed the recommended threshold of 0.7 [46], signifying good internal consistency of latent variables. This suggests that the questionnaire questions were reliable and consistent in measuring the intended constructs. It provides confidence that the data accurately reflects the underlying constructs of interest. Additionally, AVE values surpass the suggested threshold of 0.5, indicating that measurement items effectively explain the constructs [46].

Subsequently, we assessed the reliability of the indicators by calculating the outer loadings using SmartPLS 4.0 software. Table 5 presents that each indicator loading value exceeds the threshold of 0.7, implying that the latent construct accounts for more than half of the variance in each indicator [46]. Additionally, we employed percentile bootstrap with 5000 subsamples to further confirm the statistical reliability of the loadings. The fact that all p values for outer loadings are significantly below the 0.05 threshold indicates strong validity. Moreover, we applied the Fornell–Larcker criterion to assess the discriminant validity [40]. Results show that the AVE for each latent variable exceeds its correlation with other latent variables (See Table 6).

Table 6 Discriminant validity (Fornell–Larcker criterion)

	ATT	ILSS	PBC	SMIS	SN
ATT	0.819				
ILSS	0.817	0.858			
PBC	0.712	0.734	0.823		
SMIS	0.721	0.749	0.740	0.806	
SN	0.765	0.787	0.690	0.738	0.823

Table 7 Structural model analysis results of R^2 and Q^2

Endogenous latent constructs	R^2	Q^2
ATT	0.520	0.340
SN	0.542	0.356
PBC	0.547	0.364
ILSS	0.759	0.549

In conclusion, the validity of the proposed structural model can be effectively assessed using the data obtained from this questionnaire, given its internal consistency, convergent validity, discriminant validity, and reliability.

Structural model assessment

Following the analysis and validation of the measurement model, estimating the structural model is the next crucial step in assessing the validity of proposed hypotheses in structural equation modeling [89]. In this phase, we examined the standardized path coefficients to evaluate the strength and direction of the relationships between latent constructs and test the validity of the proposed hypotheses.

First, Table 7 presents the R^2 and Q^2 values of our research model. For the recommended threshold of R^2, Chin [31] suggested that the R^2 values 0.19, 0.33, or 0.67 indicate weak, moderate, or substantial correlation, respectively, in a regression model. However, Hair et al. [47] argued for higher R^2 thresholds to indicate substantial (0.7), moderate (0.5), and weak (0.25) levels of correlation in the context of marketing issues. According to this rule, the structure of ILSS2 ($R^2=0.759$) exhibits substantial correlation, while the structures of ATT ($R^2=0.520$), SN ($R^2=0.542$), and PBC ($R^2=0.547$) demonstrate moderate correlation. In terms of the model's predictive relevance, we run the blindfolding test to calculate the Q^2 value. As shown in Table 7, the Q^2 values for ATT, SN, PBC, and ILSS are 0.340, 0.356, 0.364, and 0.549 respectively. Therefore, predictive relevance was established as all of the Q^2 values were over 0 [31]. Moreover, as suggested by Hair et al. [48], Q^2 values greater than 0.35 indicate strong predictive relevance, hence, our model demonstrated strong predictive relevance our model demonstrated strong predictive relevance for the endogenous constructs.

After conducting the R^2 and Q^2 analysis, we performed two-tailed bootstrapping with 5000 resamples and a significance level of 0.05 to test the proposed hypotheses. The results are reported in Table 8. The result showed that the customer's intention for live-streaming shopping is significantly impacted by attitudes toward live-streaming shopping (H1: $\beta=0.388$, $t=9.409$, $p=0.000$), subjective norms (H2: $\beta=0.264$, $t=6.088$, $p=0.000$), perceived behavioral control (H3: $\beta=0.160$, $t=3.934$, $p=0.000$), and social media influencer streamers (H4: $\beta=0.155$, $t=3.429$, $p=0.001$). At the same time, proposed SMISs' influence on attitudes toward live-streaming shopping (H5: $\beta=0.721$, $t=19.913$, $p=0.000$), subjective norms (H6: $\beta=0.736$, $t=21.498$, $p=0.000$), and perceived behavioral control (H7: $\beta=0.740$, $t=23.738$, $p=0.000$) are confirmed. Furthermore, we examined the indirect effects within the model, and the results are presented in Table 9. The data, validated through path coefficient tests, substantiate our research hypotheses.

Discussion

The objective of this study is to investigate the factors influencing consumers' choice of live-streaming shopping as an online shopping channel. To achieve this aim, we collected 385 representative data from four regions through a questionnaire survey. The data analysis allowed us to validate the proposed research model and hypotheses. Specifically, we examined the effects of attitudes toward live-streaming shopping, subjective norms, perceived behavioral control, and SMISs on the consumer's intention for live-streaming shopping. Additionally, we tested the relationships between the newly introduced SMISs variable and attitudes toward live-streaming shopping, subjective norms, and perceived behavioral control. The results indicated that all seven of our proposed hypotheses were supported.

Table 8 Path coefficients and results for the hypotheses

Hypothesis	Path	Path coefficient	T statistics	*P* values	Result
H1	ATT -> ILSS	0.388	9.409	0.000	Supported
H2	SN -> ILSS	0.264	6.088	0.000	Supported
H3	PBC -> ILSS	0.161	3.924	0.000	Supported
H4	SMIS -> ILSS	0.155	3.429	0.001	Supported
H5	SMIS -> ATT	0.721	19.913	0.000	Supported
H6	SMIS -> SN	0.736	21.498	0.000	Supported
H7	SMIS -> PBC	0.740	23.738	0.000	Supported

Table 9 Total indirect effect and specific indirect effects

Path	Indirect effects	T statistics	*P* values
SMIS -> ILSS	0.594	13.688	0.000
SMIS -> ATT -> ILSS	0.280	8.223	0.000
SMIS -> SN -> ILSS	0.194	5.647	0.000
SMIS -> PBC -> ILSS	0.119	4.017	0.000

Firstly, our findings validate the applicability of the TPB model in predicting individual behavioral intentions in the context of live-streaming shopping. This not only reaffirms the predictive power of the TPB model in emerging online shopping formats but also provides new evidence supporting behavioral research in the live-streaming shopping domain. Specifically, in our study, the model explained a substantial portion of the variance in the consumer's intention to choose live-streaming shopping, with an R2 value of 0.759. It indicates that approximately 75.9% of the variance in the intention to adopt live-streaming shopping can be explained by the independent variables in our model. This high R2 value demonstrates the strong explanatory power of our model, suggesting that attitudes toward live-streaming shopping, subjective norms, perceived behavioral control, and SMISs collectively have a significant impact on the consumer's intention for live-streaming shopping. These findings are consistent with previous research in the field, which has also highlighted the significant role of the TPB components in predicting consumer behavior. For example, similar studies by Apasrawirote and Yawised [7] and Joo et al. [56] reported comparable R2 values, reinforcing the robustness of our results. Therefore, our proposed model demonstrates strong explanatory power.

Furthermore, we extended the TPB model by incorporating SMISs as a new variable. Previous studies, such as those by Joo et al. [56], Masukujjaman et al. [80], and Zhou and Liu [108] had introduced different new variables to extend the TPB model but focused mainly on the direct relationship between the new variables and behavioral intention. In our study, we proposed that SMISs not only directly influence consumers' behavioral intention but also impact the original three components of the TPB model. This research direction differs from previous studies. Thus, we tested the explanatory power of SMISs. The R2 values for the influence of SMISs on attitudes toward live-streaming shopping, subjective norms, and perceived behavioral control were 0.520, 0.542, and 0.547, respectively. These results confirm the effective influence of SMISs on these constructs, thereby supporting our hypotheses regarding the relationships involving SMISs. This finding provides a new perspective for the enhancement and application of the TPB model.

Secondly, through further analysis, we found that while attitudes toward live-streaming shopping, subjective norms, and perceived behavioral control all have significant positive impacts on the consumer's intention for live-streaming shopping intentions, with attitudes toward live-streaming shopping having a more pronounced effect. This may be due to the limitation of not being able to physically touch products in live-streaming shopping, making consumers' positive perceptions of the seller, such as trust [53], perceived values [81], and enjoyment [63], important prerequisites for purchasing behavior. As noted by Ho et al. [50], these positive perceptions essentially reflect consumers' attitudes toward live-streaming shopping. Our results thus reaffirm that consumers' attitudes toward live-streaming shopping behavior are crucial determinants of whether the behavior occurs. It is noteworthy that in the study of consumers' impulse buying intentions in live streaming, although these three variables are positively related to behavioral intention, Li and Kang [66] pointed out that consumers' attitudes have the least impact on behavioral intention compared to subjective norms and perceived behavioral control. This suggests that when facing different purchasing behaviors, such as impulse buying or rational buying, consumers consider different factors to varying degrees. This offers an intriguing direction for future research.

Lastly, our findings contribute to the existing literature by confirming the significant impact of SMISs on attitudes toward live-streaming shopping, subjective norms, and perceived behavioral control. In previous study, Barta et al. [13] noted that social media influencers, as unique symbols of social media, have a distinctive influence on consumer behavior. This influence mainly stems from the ability of social media influencers to establish reciprocal relationships with consumers, making it easier for consumers to psychologically trust and accept them. In this sense, social media influencers can directly affect consumers' cognitive states. Our study found that when social media influencers participate in live-streaming shopping activities as streamers, their positive perceptions by consumers naturally influence the formation of consumers' attitudes towards the behavior. Therefore, we can say that SMISs can affect consumers' attitudes toward live-streaming behaviors. This hypothesis was validated by data, as the path SMIS -> ATT -> ILSS showed significant correlations. This result can assist marketers in formulating marketing strategies, suggesting that collaborating with SMISs is an effective method to attract consumers.

Additionally, previous research emphasized that the social influence exerted by social media influencers can affect consumers' behavioral intentions. Our findings further validate how this social influence impacts consumers' behavioral intentions in live streaming. Specifically, we found that as more social media influencers join the live-streaming industry and become streamers, their fans are likely to engage in live-streaming behaviors due to their affinity for these influencers. As more people choose live-streaming shopping, a social trend or subjective norm is formed. Consequently, when consumers consider choosing an online shopping method, this subjective norm influenced by SMISs impacts their behavioral intention.

Moreover, our study also confirmed that in live-streaming shopping, SMISs can influence consumers' perceived behavioral control. Previous research on perceived behavioral control focused on individuals' ability to perform the behavior. In this study, we found that on one hand, consumers have complete autonomy to choose the live-streaming shopping activities they want to join based on their preferences, reflecting their ability to decide whether to engage in that behavior. On the other hand, due to the popularity of SMISs among fans, SMISs can indirectly influence the choices of these consumers. In this way, the impact of SMISs on perceived behavioral control occurs, indicating that in highly interactive live-streaming shopping scenarios, the influence between streamers and consumers is intertwined. This finding further enriches the existing research on perceived behavioral control.

Implications

Theoretical implications

This study contributes to two main theoretical areas. Firstly, it expands our understanding of the factors influencing consumers' choice of live-streaming shopping as an online shopping method in China. Specifically, the study reaffirms the effectiveness and applicability of the TPB model in predicting consumer behavior in the context of livestreaming commerce. Moreover, by introducing SMISs as an additional independent variable within the existing theoretical framework, we have enhanced the theoretical model to more accurately predict consumer behavior in the live-streaming shopping scenarios. According to the new model, we propose that influencers not only directly influence consumers' behavioral intentions but also indirectly affect final behavioral intentions through their influence on attitudes, subjective norms, and perceived behavioral control.

Secondly, our research findings contribute to the refinement of existing studies on consumer behavior within the context of livestreaming. Unlike previous studies that focused on factors influencing consumers' behavioral intentions during live-streaming shopping, we emphasize the beginning of the entire purchasing journey: why consumers choose live-streaming shopping in the first place. Therefore, our research theoretically enhances the study of the entire process of consumer live-streaming shopping. Additionally, the introduction of the concept of SMISs enables a deeper and more comprehensive investigation into the influence of different types of streamers on consumer behavior. Apart from their influence on consumers themselves, our research findings demonstrate that the inherent social influence of SMISs also generates corresponding social norms, thereby influencing consumers' behavioral intentions. This further enhances our understanding of the role of SMISs in the live-streaming economy.

Practical implications

Our research findings also hold practical value. Firstly, businesses implementing live streaming as their online market strategies should consider collaborating more with SMISs. On one hand, such collaborations can leverage SMISs' influence to attract more potential consumers to do live-streaming shopping. On the other hand, the presence of SMISs reduces consumers' concerns about product quality and after-sales service in live-streaming shopping, thereby reducing excessive return rates. Additionally, the findings of this study can provide insights for businesses and platforms in nurturing live-streaming streamers. The reason why SMISs wield such influence is that consumers already have a positive perception of them before engaging in live-streaming shopping. Therefore, businesses should not simply regard streamers as e-commerce salespersons but should instead recognize the unique social characteristics of live-streaming platforms and tailor their approach accordingly. Once streamers have established a certain level of social influence, they can effectively build strong relationships with consumers, thereby influencing consumer behavior and maximizing the economic benefits of live streaming.

Limitations and future research directions

This study has several inevitable limitations that future research should address. Firstly, the primary limitation lies in the relatively small sample size and its specific mainland Chinese context, which limits its generalizability. Future researchers should explore the influence of SMISs in different cultural contexts and obtain diverse samples to validate these findings. Additionally, future research could also delve into whether different cultural factors may moderate or mediate the relationships proposed in this study.

Secondly, the online questionnaire used in this study has inherent flaws, including biases in understanding questions, vague scale designs, and respondents' intentional misreporting, all of which can affect the validity of the data. Therefore, in data collection, future studies should consider employing experimental data collection methods to enhance the quality of the data. Although this study divided the entire Chinese market based on areas, only one region was selected for questionnaire distribution in each area, rendering the obtained sample insufficient to fully represent the overall trend. In future research, a more precise definition of the sample framework should be considered during sample selection, taking into account the influence of different socio-economic development levels on consumer behavior, thus making the sample more representative. Moreover, this study did not investigate whether these demographic variables also influenced customer behavioral intentions. Especially, different generations exhibit different consumer perspectives, which profoundly affect their consumption patterns. This aspect is also worth further investigation in future studies.

Thirdly, although the sample size calculation process in this study adheres to standard social science research requirements, the resultant sample size may be insufficient. Specifically, in the context of the Chinese market, where the number of consumers engaging in online shopping is substantial, using a sample of 385 respondents to represent 845 million consumers presents certain limitations. Therefore, future research should consider increasing the sample size to achieve more representative and generalizable conclusions.

Lastly, although we have examined the factors influencing the customer's intention for live-streaming shopping, we have not investigated the transition from intention to actual action. It is noted that actual consumer behavior is influenced by various factors. Therefore, whether the formation of consumer behavioral intention implies the inevitable occurrence of actual behavior remains a topic that requires further research. Future researchers should consider the transition from behavioral intention to actual behavior as a valuable research topic.

Conclusions

In conclusion, to enhance the existing research on consumers' intentions regarding live-streaming shopping, this study focuses on the determinants of the consumer's intention for live-streaming shopping. The TPB model was employed to validate the relationships, and the model was extended by incorporating SMIS as a new variable. An analysis of data from 385 questionnaires confirmed that consumers' intentions for live-streaming shopping are significantly influenced by their attitudes toward live-streaming shopping, subjective norms, perceived behavioral control, and SMISs. Additionally, SMISs positively impact consumers' attitudes toward live-streaming shopping, subjective norms, and perceived behavioral control regarding live-streaming shopping. These results not only validate the applicability of the TPB model in the context of live-streaming shopping but also identify SMIS as a crucial factor influencing the consumer's intention to engage in live-streaming shopping.

Abbreviations

SMISs	Social media influencer streamers
TPB	Theory of planned behaviour
TRA	Theory of reasoned action
CNNIC	China Internet Network Information Center
CCA	China Consumers Association
NBSC	National Bureau of Statistics of China
ATT	Attitudes toward live-streaming shopping
SN	Subjective norms
PBC	Perceived behavioral control
ILSS	Intention for live-streaming shopping
VIF	Variance inflation factor
AVE	Average variance extracted

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Author contributions
JYL drafted and revised the manuscript, conducted model construction, methodological research, and performed tasks related to data collection, analysis, and visualization. NZ reviewed the manuscript and provided supervision; XJM was responsible for data curation and visualization. All authors have read and agreed to the published version of the manuscript.

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Availability of data and materials
The datasets used and analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate
The questionnaire was assessed and approved by Universiti Teknologi Malaysia. An informed consent form signed by Universiti Teknologi Malaysia was provided to every participant before the survey. All data remains confidential.

Consent for publication
Not applicable.

Competing interests
The authors declare that they have no competing interests.

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