Inducing Shoppers’ Impulsive Buying Tendency in Live-Streaming: Integrating Signaling Theory with Social Exchange Theory

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Abstract

Purpose – The increasing popularity of live-streaming commerce has provided a new opportunity for e-retailers to boost sales. This study integrated signaling theory and social exchange theory to investigate how streamer- and product-centered signals influence customers’ likelihood of making an impulsive purchase in the live-streaming commerce context.

Design/methodology/approach – An online survey was designed and distributed to the target respondents in China using purposive sampling. A total of 735 valid responses were analyzed with partial least square structural equation modeling (PLS-SEM).

Findings – Both streamer-centered signals, i.e., streamer credibility and streamer interaction quality, were discovered to significantly influence product-centered signal, i.e., product information quality. Additionally, streamer interaction quality was found to have a significant impact on streamer credibility. Furthermore, it was observed that customer engagement played a significant mediating role in the relationship between product information quality and impulsive buying tendency. Moreover, the paths between product information quality and customer engagement, as well as the connection between engagement and impulsive buying tendency, were found to be moderated by guanxi orientation.

Originality/value – Despite the prevalence of impulsive purchases in live-streaming commerce, few studies have empirically investigated the impact of streamer and product signals on influencing customers’ impulsive purchase decisions. Consequently, to the best of our knowledge, this study distinguishes itself by offering empirical insights into how streamers use reciprocating relationship mechanisms to communicate signals that facilitate impulsive purchase decisions.

Keywords: Live-streaming commerce; Signaling theory; Social exchange theory; Customer engagement; Impulsive buying tendency; PLS-SEM.

Paper type Research paper

1. Introduction

Live-streaming commerce (LSC) is a new form of e-commerce platform, which works by establishing a temporary virtual community shared by streamers and customers in real-time (Luo et al., 2023). Its increasing popularity has prompted e-retailers to leverage live-streaming for product promotion, with an anticipated 20.3% annual growth in the global live-streaming market from $1.03 billion in 2021 to $1.23 billion in 2022 (The Business Research Company, 2023). According to an industry report, LSC holds substantial potential in stimulating impulsive buying, as 66.2% of customers reported making impulsive purchases, largely
influenced by streamers’ recommendations in LSC (iiMedia, 2021). Streamers play a pivotal role in this unique shopping environment, surpassing the impact of traditional marketing messages, as the immediacy and interactive nature of LSC enhances the streamer’s role in guiding customers to make impulsive purchase decisions (Yang et al., 2023a; Miranda et al., 2024). Understanding these dynamics is essential for businesses and marketers to leverage LSC fully as a channel for impulsive buying behavior (Yan et al., 2022).

Existing studies in the field of LSC have predominantly focused on a few specific areas, leaving gaps in the exploration of other relevant factors that may potentially trigger impulsive buying within LSC. For example, most studies have applied stimulus-organism-response theory (SOR) to examine external stimuli such as technical characteristics of the platform (e.g., presence, immersion, media richness), marketing stimuli (e.g., sales promotions, scarcity, product popularity), and customer motivations (e.g., hedonic/utilitarian value, flow, entertainment) in driving impulsive buying through customer internal states (e.g., emotional or cognitive reactions) (Lin et al., 2023; Parsad et al., 2021). However, given the importance of the awareness effect of recommendations and the unique nature of LSC in stimulating individuals’ impulsive consumption, there is an urgent need to understand the role of streamer recommendations as a primary signal in triggering impulsive purchases (Lu and Chen, 2021; Luo et al., 2024).

In light of this, the present study integrates signaling theory with social exchange theory (SET) to develop a comprehensive model aimed at exploring the factors influencing impulsive buying tendencies across various domains. Responding to Lo et al.’s (2022) call for investigating effective streamer criteria in impulsive buying, this study examines the role of streamers in transmitting information and explores how the exchange of information between streamers and customers can lead to high levels of engagement with the LSC, ultimately fostering impulsive buying tendencies. On the other hand, product signals are identified as another crucial factor (Chen et al., 2019). This concept is motivated by the assertion that the product information not only serves as the primary signal for customers to evaluate the functionality and quality of a product but also acts as a filtering mechanism within the first few minutes to determine whether it is worthwhile to continue watching the LSC (Yang et al., 2023b; Liu et al., 2023). Generally, LSC content that provides customers with informative and exceptional details is more likely to evoke positive perceptions, thereby expediting the customer’s decision-making process (Lo et al., 2022; Shamim and Islam, 2022). Hence, the research model of this study draws attention to how multi-layered influence can further trigger impulsive buying. Specifically, the former content (i.e., streamer signals) aims to enhance
positive perceptions of the streamer, including both streamer interaction quality and streamer credibility. Meanwhile, the latter content (i.e., product signals) focuses on communicating positive attributes of the product (Mavlanova et al., 2016), which can be assessed using product information quality.

Considering the social nature of LSC, which prioritizes the establishment of social relationships, this study extends the applicability of SET to examine customer engagement as an internal mechanism that fosters impulsive buying tendencies. By immersing customers in the dynamic content of LSC, engaged customers are more likely to encounter decision points, such as product recommendations with limited-time offers (Chen et al., 2022a). Consequently, streamers can seamlessly integrate impulsive buying opportunities into the customer experience itself (Luo et al., 2024). This intermediary role, grounded in SET, highlights the significance of reciprocal relationships in transforming customers from passive information receivers to active information-seekers. This offers a nuanced understanding of how engaged customers actively explore latent needs and make impulsive purchase decisions (Hollebeek, 2011; Hollebeek et al., 2021). Therefore, it is crucial for our study to consider the mediating role of customer engagement in triggering impulsive buying.

Given that this study is conducted in China, the concept of guanxi, which represents Chinese social networks, holds significant importance in transactional outcomes (Su et al., 2021). Prior research has indicated that customers with a guanxi orientation prioritize reciprocity (Wang et al., 2014) and inherently trust those with established guanxi connections (Luo, 1997; Ding et al., 2017). Aligned with SET, guanxi orientation contributes to positive moderation effects on individual attitudes and behavior (Cropanzano et al., 2017). The nature of LSC fosters communities around shared interests, which aligns with guanxi's emphasis on social harmony and conformity to group norms (Wu et al., 2021). The inherent trust stemming from guanxi reduces the need for detailed information evaluation in LSC, thereby heightening susceptibility to impulsive buying based on streamer recommendations (Zhang et al., 2019b). Therefore, our study delves into the nuanced role of guanxi orientation as a moderator, exploring how it distinctly influences the signaling process, leading to impulsive buying tendencies through heightened social exchange.

Based on the abovementioned, this study aims to provide streamers with some implications, particularly about creating a more engaging environment by using information signals to motivate impulsive buying tendencies. Next, the literature review will be presented in section 2, followed by the development of the conceptual model and the hypotheses...
development in section 3. Next, in sections 4 and 5, we will discuss the methodology and results. Finally, we conclude the main findings and implications in section 6.

2. Theoretical foundations
The study draws on both signaling theory and SET as informing theories to study customer impulsive buying tendency in LSC (Przepiorka and Berger, 2017; Chen et al., 2019; Tóth et al., 2022). Within these theoretical realms, we highlight how streamers and customers looking to form relationships evaluate their exchanges' estimated benefits and costs using available signals. Both theoretical bases integrated well to explain online social exchange and to solve information asymmetry between customers and streamers.

2.1 Signaling theory
Signaling theory, originating from information economics studies, addresses situations characterized by asymmetric information, where two parties possess varying levels of information (Spence, 1974; Connelly et al., 2011). Existing literature on signaling theory underscores those signals, which disclose relevant and valuable product information from one party to another and significantly reduce uncertainty and facilitate a purchase or exchange (e.g., Lu and Chen, 2021; Wells et al., 2011). Beyond product signals, research suggests that strategically employed hidden signals by signalers play a pivotal role in emotional and unplanned buying situations (Chen et al., 2019; Przepiorka and Berger, 2017). In line with the aims of this study, signaling theory is adopted to discern potential hidden signals and explore their interplay with product signals in triggering impulsive purchases.

Within the LSC context, signals emerge as a pivotal determinant in triggering impulsive purchase decisions (Shamim and Islam, 2022). This significance arises from LSC's facilitation of product discovery through pre-curated presentations by streamers, fostering exploratory and less-focused buying behavior, leading to unplanned purchases (Fu and Hsu, 2023; Liu et al., 2023). Given the constraints of limited time and cognitive resources in decision-making processes, signaling serves as a rapid cue for processing information, aiding customers in making impulsive decisions (Miranda et al., 2024; Chen et al., 2019). Therefore, it is imperative for streamers to strategically invest in signals to convey valuable information, diminish uncertainty, and facilitate impulsive purchases (Connelly et al., 2011).

Previous research has shown that signals related to product- and seller-quality are vital in alleviating uncertainties in online selling, thereby promoting impulsive purchases (Chen et al., 2016). With the paradigm shift introduced by LSC, the study recognizes the transformative
role of streamers’ credibility and real-time interactions in creating an authentic shopping environment, effectively reducing uncertainties, and prompting impulsive purchases (Fu and Hsu, 2023; Miranda et al., 2024). Building upon Chen et al.’s (2019) typology for quality signals, this study categorized the signals conveyed by streamers into streamer-centered signals and product-centered signals.

2.1.1 Streamer-centered signals
Streamer-centered signals, conveyed through non-product-centered content, aim to enhance positive perceptions of the streamer (Mavlanova et al., 2016; Lu and Chen, 2021). Previous research has shown unobservable streamer reputation and service quality serve as hidden signals (Zhang et al., 2020), heuristically affecting judgments about product quality, thereby reducing uncertainty and prompting impulsive purchases (Wang and Scheinbaum, 2018; Yang et al., 2023a). Hence, in this study, streamer credibility and streamer interaction quality are regarded as streamer-centered signals.

Streamer credibility refers to the positive characteristics of streamers that lead to customers’ accepting the veracity of their messages (Ohanian, 1990). It is an important evaluation criterion of product information quality, especially in online selling (Ismagilova et al., 2020). In the LSC context, streamer credibility is determined by two subdimensions: expertise (streamers’ relevant knowledge, experience, and skills) and trustworthiness. (streamers’ honesty, credibility, and integrity) (Hovland and Weiss, 1951). On one hand, streamer interaction quality refers to customers’ perceptions of the interaction quality with streamers in live-streaming shopping (Zhang et al., 2020; Tseng et al., 2021). Unlike the physical scene, the interaction of the live-streaming shopping scene relies on the effectiveness of technology (Etemad-Sajadi, 2016; Yan et al., 2022). Thus, this study conceptualized streamer interaction quality based on three subdimensions, i.e., real-time interaction, responsiveness, and empathy. Real-time interaction refers to the real-time communication between the streamer and customer; Responsiveness refers to how streamers respond to customers’ questions and inquiries in a timely and accurate manner; Empathy relates to streamers’ caring and individualized attention to customers (Zhang et al., 2020; Zhang et al., 2022).

2.1.2 Product-centered signal
Product-centered signals reveal direct information about the recommended product and mainly focus on conveying positive attributes of the product (Eppler, 2006). Within the context of LSC,
it refers to customers’ perception of product information quality, which is often evaluated based on how well it aligns with their expectations and fulfils their needs (Zhang et al., 2020).

Adapting to the LSC context, this study conceptualized product information quality using three subdimensions: believability, usefulness, and vividness (Zhang et al., 2020). Believability refers to the authenticity and credibility of the product information conveyed by the streamer. Customers assess whether the information presented by the streamer is trustworthy and reliable. Usefulness pertains to customers' perception of how valuable the new information provided by the streamer is in enhancing their understanding of the product. Customers assess whether the information presented by the streamer is practical and relevant to their decision-making process. Vividness refers to the sensory richness of the information presented by the streamer. It encompasses the extent to which the streamer utilizes various sensory channels (e.g., visual, and auditory) to stimulate customers' senses and provide a more immersive and engaging experience. This may include activities such as product demonstrations or in-person examinations that offer a more tangible and vivid representation of the product. Taken together, these dimensions of product information quality capture customers' evaluations of the authenticity, usefulness, and sensory stimulation provided by the streamers in the LSC context.

2.2 Social Exchange Theory (SET)

Social Exchange Theory (SET) proposes that interpersonal relationships occur when one party exchanges something valuable with the other party. This exchange can involve economic resources or social resources such as information, support, and influence (Cropanzano and Mitchell, 2005). Previous research has examined the impact of economic rewards (e.g., coupons) on review posting intentions, attitudes, and usage intentions (e.g., Shiau and Luo, 2012; Tang et al., 2016). Additionally, studies have explored how social exchanges, such as information and support, influence brand engagement, customer perception, trust, and purchase intention (Phan et al., 2020; Tóth et al., 2022).

Within the existing literature, SET is mainly used to investigate three aspects: the initiation of reciprocal actions (e.g., providing information support), the process of reciprocity (e.g., the formation of relationships between parties), and reciprocating responses (e.g., attitudinal and behavioral outcomes). Additionally, positive reciprocity belief has been studied as a moderator in these contexts (Cropanzano et al., 2017). In the context of LSC, first, understanding SET is crucial in comprehending how the exchange of information serves as an initiating action that triggers reciprocal exchanges between streamers and customers (Zhang et
For example, when customers find the information shared by streamers to be valuable, credible, and vivid, this triggers positive emotions like confidence and excitement, motivating them to invest in building an emotional connection with the streamer (Hollebeek et al., 2019). Given the interactive nature of customer engagement, SET is an appropriate theory to explain customer engagement as a reciprocating relationship mechanism between streamers and customers, which leads to positive behavioral outcomes (Hollebeek, 2011; Rather and Sharma, 2019).

Second, customer engagement can be seen as a social exchange (reciprocating process) between customers and streamers. Customers invest their time and attention with the expectation of gaining social and personal benefits like information, entertainment, a sense of community, and emotional satisfaction (Hollebeek, 2011; Rather and Sharma, 2019). Consequently, impulsive buying is the reciprocating response when these expectations align with the product recommendations presented in LSC (Chen and Yao, 2018; Chen et al., 2022a). Besides, when customers find the information provided by a streamer to be actionable and helpful, they will invest more effort (e.g., discussions and sharing experiences). This reciprocating process can indirectly influence impulsive buying by creating a sense of community and emotional satisfaction (Ou et al., 2022). Moreover, when customers find the streamer’s information valuable and credible, customers’ social resources invested during interaction (e.g., through co-creation, sharing of product-centered experiences, etc.) can further enhance impulsive buying tendencies (Hollebeek et al., 2019; Danniswara et al., 2020).

Third, positive reciprocity beliefs, as discussed in Cropanzano et al.’s (2017) review of SET, may act as a potential moderator that influences individuals’ attitudes and behaviors. Guanxi orientation, as a form of positive reciprocity belief deeply rooted in Chinese culture, moderates individuals’ attitudes and behaviors by fostering trust, reciprocity, emotional connections, and enhanced persuasion (Ding et al., 2017; Su et al., 2021). Building on the literature, this study utilizes SET to predict guanxi orientation’s positive moderation effects on customer engagement and their impulsive purchase decisions.

2.3 Impulsive Buying Tendency
Impulse buying typically occurs in the spur of the moment, often prompted by stimuli encountered during the shopping experience (Beatty and Ferrell, 1998). In contrast, planned buying is a more deliberate process involving careful consideration before purchase. In live-streaming commerce, impulse buying is triggered by unique environmental cues such as limited broadcast time, real-time interaction with persuasive streamers, and their vicarious product
demonstrations, which create urgency and connection with shoppers (Lo et al., 2022; Luo et al., 2024). This notion contrasts with traditional e-commerce, where shoppers consider product alternatives for planned purchases. Subsequently, they must meticulously evaluate and analyze information before making a decision (Wang et al., 2024). While both involve cognitive processes, they differ in processing depth and cognitive effort (Chen et al., 2019). In the LSC context, we define “impulsive buying tendency” as the buying behavior which occurs when customers enter a broadcasting room and unexpectedly develop a strong desire to buy after watching a broadcast (Lu and Chen, 2021).

Impulse buying is typically classified into four categories: pure, reminder, planned, and suggestive (Stern, 1962), which has served as a foundational framework for research in this area (Beatty and Ferrell, 1998; Rook, 1987). This classification also applies to most buying behavior observed on LSC platforms (Xu et al., 2020). For instance, when customers aimlessly watch streamers' real-time product demonstrations and decide to purchase, it falls under the category of pure impulsive buying. If they recall a shortcoming or a prior experience while watching the broadcast and make a purchase, it is considered a reminder of impulsive buying. Suggestive impulsive buying occurs when customers purchase a new product based on streamers' recommendations, such as suggesting different occasions for product use. Finally, when customers watch streamers' product demonstrations with a shopping list but make purchases based on coupons or promotions, it can be categorized as planned impulse buying (Xu et al., 2020; Chan et al., 2017).

In the existing literature, some studies suggest that impulse buying tendency is a kind of personality trait of individuals (Verplanken and Herabadi, 2001), a leaning entrenched (Parsad et al, 2021). This trait reflects their general inclination to make unplanned purchases driven by emotions or other psychological factors. It is imperative to acknowledge that unplanned purchases can be influenced by the interplay of a wide range of situational, environmental, and contextual factors (Chen et al., 2019; Fu and Hsu, 2023). Based on our definition of impulsive buying (four types of impulsive buying proposed by Stern, 1962) in the LSC context, streamer recommendations can result in customers’ impulsive purchases. This entails a sudden, strong, and enduring desire to purchase immediately when frequently exposed to information and interactions with streamers (Chen et al., 2016; Yang et al., 2023b).

However, most studies mainly examined the effects of content quality on regular purchases because it mainly involves cognitive evaluation (e.g., Gao et al., 2021; Liu et al., 2022). ignoring that information quality in LSC is more customer-centric (responsiveness and personal attention) and visualized (vs. product-centric textual description), thus customers'
responses encompass not just cognitive reactions but also emotional, behavioral, and social reactions, all of which contribute to the activation of impulsive buying tendencies. Lastly, similar to the argument posited by Lee and Kacen (2008), information available inside a store will have a greater overall impact on an impulse purchase than a planned purchase. Thus, if streamer recommendation was only available during the broadcast, it became a more important factor in impulse buying than in the regular buying context.

3. Research model and hypotheses
Based on the signaling theory and the SET, this study explores the intricate dynamics between streamers and customers in the context of reciprocal relationship mechanisms and impulsive purchase decisions in LSC. Additionally, we employ guanxi orientation as a potential moderator that may alter the relationship between the proposed factors. Prior research in the online marketing domain found that customers’ online purchase decisions may vary based on their demographic profiles such as gender, education, and income (Chen et al., 2022b), and their past shopping experiences (i.e., usage duration and purchase frequency) (Mallapragada et al., 2016). Thus, this study included these as control variables to avoid any spurious effects on impulsive buying tendency. Figure 1 depicts the proposed conceptual framework.

[Insert Figure 1 here]

3.1 Signals and customer relationship mechanism
In the LSC context, streamer interaction quality helps customers to better evaluate streamer credibility. Real-time and interactive communication aids customers in identifying the service personnel featured on-screen (Wongkitrungrueng and Assarut, 2020). Additionally, frequent interactions between the streamer and customers can lead to increased familiarity (Chung and Cho, 2017) and the cultivation of a trustworthy relationship (Guo et al., 2021). Consequently, this allows customers to establish a better assessment of the level of trustworthiness and expertise of streamers (Onofrei et al., 2022). On the other hand, by benefiting from the existence of bullet-screen comments (i.e., real-time reviews posted by customers), streamers can provide timely responses to customers’ questions and provide individual attention to different customers (Kang et al., 2020). As a result, streamers’ better understanding of customer needs enhances their relationship with customers and evidences their credibility (Gong and Li, 2019). Drawing upon these arguments, we hypothesize that the better the streamer’s interaction quality, the higher the perceived streamer credibility.
H1: Streamer interaction quality positively affects streamer credibility.

According to signaling theory, streamer credibility serves as a streamer-centered signal that reduces customers’ uncertainty about the product and positively influences customer’s evaluation of product information quality (Mavlanova et al., 2016; Naujoks and Benkenstein, 2020; Chung et al., 2020). Information from credible sources is perceived to be a more valid and persuasive heuristic cue (Wang and Scheinbaum, 2018), which positively influences individual beliefs, opinions, and attitudes (Yan et al., 2022). Studies proved that streamers’ expertise and trustworthiness positively influence customers' perceived usefulness of information (Ma, 2021; Guo and Sun, 2022). Moreover, customers’ trust in streamers is more likely to transfer to the product endorsed (Leite and Baptista, 2022; Chung and Cho, 2017). In live-streaming shopping, when customers perceive streamers as highly credible, they will certainly have more confidence in the quality of the information content (Kang and Namkung, 2019; Chen et al., 2022b). Besides, streamers are often considered experts who are more familiar with products and experienced in providing shopping guidance (Zafar et al., 2021). Therefore, we propose streamer credibility may strongly shape the quality of information. The following is proposed:

H2: Streamer credibility positively affects product information quality.

Relying on both the real-time and visibility characteristics of live-streaming, customers receive quick and effective responses from streamers without the barriers of time and space (Wang et al., 2022; Zhang et al., 2020). By interacting with a streamer in real-time, customers can fully understand the product details (e.g., place of origin, quality, and price) (Xue et al., 2020). Meanwhile, the interactive product presentation feature also improves customers’ sense of experience (Singh et al., 2021; Yang et al., 2023a) and provides them with vivid product information (Guo and Sun, 2022). In addition, a personalized feature found in the LSC platform allows the streamers to provide customers with a better shopping experience and highly improved communication efficiency (Zhang et al., 2022). Grounded on the signaling theory, streamer interaction quality is a seller-quality related signal, which can directly influence product-quality related signal (Mavlanova et al., 2016; Özpolat and Jank, 2015). Therefore, streamer interaction quality not only influences the convenience and pertinence of
communication but also improves the quality of information obtained. We, hence, hypothesize the following:

**H3**: Streamer interaction quality positively affects product information quality.

According to the signaling theory, symmetric information exchange between the online service provider and the customer generates positive outcomes (Connelly *et al*., 2011). For example, high-quality information provides customers with a greater shopping experience, enhancing their positive attitudes and, eventually, their engagement intentions with streamers (Wang and Huang, 2023). Most importantly, customers tend to consider the benefits and risks in deciding whether or not to engage with the streamer (Nammir *et al*., 2012). In LSC platforms, streamer provides vivid and useful information content by demonstrating product details (e.g., product materials, workmanship, and size) in front of the screen or sharing their knowledge and personal experience (Wang *et al*., 2022). As a result, customers’ uncertainty about product fit will be reduced (Al-Adwan *et al*., 2022), and they are more likely to interact positively with streamers (Hu and Chaudhry, 2020; So *et al*., 2021b). Based on the principle of social exchange, customers reciprocate with the streamer when they are able to gain benefits, hence they will develop an increased likelihood to reciprocate with engagement behaviors such as liking, sharing, subscribing, and commenting (Oh *et al*., 2017). Therefore, when the information provided by streamer is of high quality, it would drive customer engagement. Thus, we hypothesize the link between product information quality and customer engagement:

**H4**: Product information quality positively influences customer engagement.

### 3.2 Customer relationship mechanism and impulsive buying tendency

Customer engagement is the psychological state of mind in which customers are engaged subconsciously, resulting in frequent interactions beyond transactional motives in a focal service relationship (Brodie *et al*., 2019). This term can be decomposed into four components: cognitive, affective, behavioral, and social engagement (Vivek *et al*., 2014; Hollebeek, 2019).

- **Affective engagement** refers to customers’ emotional bond with the streamer.
- **Behavioral engagement** is a series of interactive behaviors such as likes, shares, and comments.
- **Cognitive engagement** relates to customers’ mental apprehension resulting from observation, learning, and communication.
- **Social engagement** highlights social and interactive
characteristics such as co-creation and sharing values between streamers and customers (Vivek et al., 2014; Dessart et al., 2016).

Previous studies have examined that positive customer engagement significantly influences consumption behaviors and decision-making (Pansari and Kumar, 2017; Alvarez-Milán et al., 2018). When cognitively engaged in live-streaming shopping, customers develop a better understanding of the recommended product, enabling them to feel a sense of gratification and form positive evaluations of impulse buying tendency (Xu et al., 2020). Besides, emotionally engaged customers are more likely to conduct hedonic buying (Nandha et al., 2017). For example, in Shen and Khalifa’s (2012) research, customers who are highly aroused in a pleasant online shopping environment tend to spend more time and effort on product exploration, which further induces impulsive purchase tendency. Moreover, customer engagement increases the intimacy between streamers and customers (Chen et al., 2019; Luo et al., 2024), meanwhile, reduces customers’ uncertainty and consumption concerns, thus positively influencing their impulsive consumption intentions (Lo et al., 2022). Based on SET, when customers gain benefits from this relationship (i.e., positive emotion, intimacy, reduction of uncertainty), they are more likely to exhibit positive emotions and impulsive buying tendency. Therefore, customer engagement acts as a force that influences customers’ impulsive buying tendency. We hypothesize that:

**H5:** Customer engagement positively affects impulsive buying tendency.

### 3.3 Mediation effect of customer engagement

Customer engagement is a psychological state in the service experience process (Brodie et al., 2019), and most scholars have used customer engagement as a mediator between customer perceptions and behavioral intentions (Rather and Sharma, 2019; Hollebeek, 2011; So et al., 2021a). Prior research evidenced that the influence of informational signals on impulsive buying tendency can be further elaborated by incorporating a psychological mechanism (Chen and Yao, 2018; Zhang et al., 2019a; Shamim and Islam, 2022). In live-streaming shopping, browsing information presented by the streamer may trigger customers’ emotional reactions, e.g., emotional connection, which also indirectly influences impulsive buying (Verhagen and Dolen, 2011; Parboteeah et al., 2009). Besides, engaging in high-quality information exchange can also drive social benefits to customers by increasing their confidence to make immediate purchase decisions and choose trusted and credible streamers (Danniswara et al., 2020; Luo et al., 2024).
As a mediating variable, customer engagement regulates changes in impulsive buying tendency. Vivek et al. (2014) have mentioned that a high degree of engagement makes customers believe that the product recommended has all the merits and makes the purchase more satisfying. As a result, customers' positive emotions from satisfaction can easily trigger impulsive buying tendency (Widagdo and Roz, 2021). Meanwhile, cognitive engagement allows the viewers to believe that the product has high value and is worth buying (Kumar et al., 2023). Therefore, we propose the following hypothesis:

**H6**: Customer engagement mediates the relationship between product information quality and impulsive buying tendency.

### 3.4 Moderation effects of guanxi orientation

Guanxi is a personalized relationship based on mutual interests and benefits, achieved through the exchange of favors between two parties (Luo, 1997). This concept revolves around the principle of reciprocity, where individuals engage in mutual give-and-take to strengthen relationships. In online business contexts, especially LSC, guanxi often involves a broader scope of connections due to the vast reach of digital platforms. The interactions in question are often more transactional-focused, emphasizing the exchange of products, discounts, and promotions (Zhang and Zhang, 2014; Parsad et al., 2021). Individuals with a strong guanxi orientation tend to have stronger exchange ideologies and pay closer attention to social interactions in order to establish close ties with those around them (Guo et al., 2021).

Grounded in SET, previous research has highlighted the role of the reciprocal norm of guanxi in moderating individual attitudes and behaviors (Cropanzano et al., 2017; Su et al., 2021; Ding et al., 2017). For instance, in the context of online shopping, individuals who benefit mutually through information sharing tend to develop positive attitudes toward engagement (Shiau and Luo, 2012). Communication within virtual communities can be seen as a form of social exchange, where voluntary actions between parties are often based on a cost-benefit approach (Dong et al., 2017; Gharib et al., 2020). In the context of LSC, customers with a higher guanxi orientation may actively engage with streamers to establish shopping convenience, believing that streamers can provide valuable and important information based on the assurance of reciprocity. During their interaction, customers and streamers can communicate, share experiences, and learn from each other (Li et al., 2020; Ou et al., 2022). Consequently, customers with a strong guanxi orientation are more likely to sustain their
engagement in live-streaming shopping when they receive valuable, high-quality information from the streamer (Barnes et al., 2011; Su et al., 2021).

Furthermore, existing research indicates that individuals with a high guanxi orientation tend to develop mutual trust with their counterparts, facilitating decision-making in online transactions (Leung et al., 2020; Lin et al., 2018). This aligns with SET, individuals with a strong guanxi orientation highly value reciprocal relationships (Wang et al., 2014; Ding et al., 2017). In the context of impulsive purchases, the favorable treatment and personalized attention associated with guanxi foster a sense of obligation, positively moderating impulsive buying through reciprocal favor exchange (Zhang et al., 2019b; Zhang et al., 2020). Moreover, guanxi orientation is a reciprocity belief based on mutual benefits. Thus, when customers engage in the flow shopping experience created by streamers, guanxi-oriented customers are more likely to trust the streamer (Zhang et al., 2019b; Su et al., 2021). Consequently, they are more inclined to reduce the cognitive deliberation process and make impulsive purchases (Wu et al., 2021). Based on these considerations, we propose the following hypotheses:

**H7a:** When customers are more guanxi-oriented, the relationship between product information quality and customer engagement is stronger.

**H7b:** When customers are more guanxi-oriented, the relationship between customer engagement and impulsive buying tendency is stronger.

### 4. Methodology

#### 4.1 Data collection procedures

During data collection, the designed questionnaires were distributed using purposive sampling – a non-probability sampling procedure – through a professional online survey service website (see https://www.wjx.cn/). The purposive sampling method was employed in this study due to the unavailability of a complete sampling frame in the given context. This approach assists in selecting valid samples and helps minimize non-response bias (Rowley, 2014). It is worth noting that both Lin et al. (2023) and Tong et al. (2022) have utilized a similar method when examining customers' impulse buying behavior in the live-streaming context. Furthermore, LSC has proven particularly effective in targeting the millennial generation, referring to customers born between 1981 and 2000, who form a significant customer group (Taobao Live and Chinese Academy of Social Sciences, 2022). Therefore, this generation represents an important and intriguing market segment for streamers who explore the LSC context. To ensure the suitability of potential respondents (i.e., Millennial live-streaming
shoppers), three pre-screening questions were included as selection criteria for our sampling technique. The first question inquired whether respondents were born between 1981 and 2000. The second question assessed whether they had subscribed to at least one social media platform that integrates live-streaming functions, such as Taobao or Douyin. The third question focused on whether they had engaged in any live-streaming shopping experiences within the last two months. Respondents who did not meet these pre-screening criteria were excluded from the study. To ensure more accurate responses, we provided a brief introduction with a shopping scenario aimed at recalling respondents' memories of their live-streaming shopping experiences.

A total of 960 responses were collected, after excluding incomplete and straight-line answers, 735 valid responses were finally confirmed. Table 1 exhibits the demographic information of the participants. Of all the respondents, the majority of them were female (54.15%), bachelor’s degree holders (40.82%) with monthly income of RMB5,001 to RMB8,000 (39.46%). Additionally, they had purchased three times in the current two months (32.79%) and their usage duration was 1 to 2 years (30.07%).

4.2 Measures

All constructs’ measurement items were adapted based on previous literature, with minor adaptations for the LSC context. As the survey was conducted in China, while all items in the survey were originally designed in English, thus we adopted the forward-back translation to ensure the accuracy of the translation (Brislin, 1970). Next, all items were assessed by a panel of eight experts comprising five marketing professors and three experienced live-streaming Millennial shoppers. They were requested to examine whether the statements in the questionnaire reflect the constructs being measured. Before the questionnaires were distributed, we conducted a preliminary test (pre-test) with 40 live-streaming Millennial shoppers. The results show that Cronbach's α coefficients of all questionnaire items in exploratory factor analysis are larger than 0.7 in the pre-test, thus all proposed items of each construct are valid and reliable (Hair et al., 2020).

The items of product information quality and streamer interaction quality were adopted from Zhang et al. (2020). Streamer credibility was measured with the scale established by Ohanian (1990). Four dimensions of customer engagement were measured: affective, behavioral, cognitive, and social, based on the scale modified by Dessart et al. (2016) and Vivik et al. (2014). Guanxi orientation was measured with the scale developed by Ding et al. (2017).
Finally, the scale of impulsive buying tendency adopted the measurement items established by Beatty and Ferrell (1998) (see Appendix A).

5. Data Analysis

5.1 Choice of data estimation technique
Firstly, SPSS v.29 was used for the assessment of respondents’ demographic profiles and test of common method bias. Secondly, partial least squares structural equation modeling (PLS-SEM) using SmartPLS v.4 (Cheah et al., 2024) was employed in the study to maximize the variance explained in the latent dependent variables and has been widely employed in information system fields (Song et al., 2021; Lim et al., 2022). Specifically, we used PLS-SEM for three reasons. First, the technique is suitable for testing models of theory building and testing (Shiau et al., 2019), which fits well with this study’s goal of integrating both signaling theory and social exchange theory. Second, there are many past studies proven that PLS-SEM is best suited for testing complex variables, i.e., higher-order constructs (Becker et al., 2023) (i.e., streamer interaction quality, streamer credibility, product information quality, and customer engagement are conceptualized as a reflective-formative type of higher-order constructs). This analysis approach is found to outperform when assessing a research model that involves many constructs and complex relationships (i.e., with mediation and moderation effects) (Cheah et al., 2021). Finally, this technique is causal-predictive, which has achieved the best balance between explanation and prediction (Shmueli et al., 2019).

5.2 Common method bias (CMB)
Given the cross-sectional approach used in the study design, CMB may be a potential concern. To assess CMB, we adopted two different CMB assessments. First, we adopted Harman’s single-factor test, and the results showed that the variance explained by the first factor was 23.779% (<40%), which suggests there is no CMB (Fuller et al., 2016). Second, the full collinearity (FC) test showed that the variance inflation factor (VIF) values were between 1.014 and 1.368 (below 3.33; see Table 2), suggesting CMB does not present a severe issue in this study (Kock, 2015).

5.3 Measurement model
To assess the measurement model, Hair et al. (2020) suggested using a confirmatory composite analysis (CCA) approach. As shown in Table 2, all metrics for the internal consistency reliability (Cronbach's alpha, ρA, and CR) were above the acceptable value of 0.7, which
satisfied the reliability requirement (Hair et al., 2020). Next, convergent validity was achieved as items’ loading was higher than the threshold of 0.708 and AVE was greater than 0.50 (See Table 2, Hair et al., 2020). The final step of measurement model assessment is to evaluate the constructs’ discriminant validity using the heterotrait-monotrait ratio of correlations (HTMT). As presented in Table 3, the HTMT scores of all constructs were lower than the conservative threshold value of 0.85, confirming discriminant validity among all the constructs used in this study (Hair et al., 2020).

5.4 Higher-order construct (HOC)

This study employed a disjoint two-stage approach to assessing four higher-order constructs (HOCs): product information quality, streamer interaction quality, streamer credibility, and customer engagement (see Becker et al., 2023). First, convergent validity was tested using redundancy analysis with a global single-item. As shown in Table 4, the path coefficient (i.e., convergent validity) of four HOCs, i.e., product information quality (0.704), streamer interaction quality (0.768), streamer credibility (0.738), and customer engagement (0.886) were greater than the threshold value of 0.70, thus confirming the validity of all HOCs (Cheah et al., 2018; Hair et al., 2020). Next, the VIF values of all LOCs were between 1.063 and 1.215 (<3.33) (Hair et al., 2020). Thus, multicollinearity is not an issue in this path model. Finally, all LOCs achieved statistically significant results with weight values between 0.126 and 0.635.

5.5 Model fit

To assess the model fit, we used both the standardized root mean square residual (SRMR) and the normed fit index (NFI). The results showed that the SRMR values for both the saturated and estimated models were 0.041 and 0.068, respectively, which were below the threshold of 0.08 (Hu and Bentler, 1999), indicating a good model fit. In addition, both the saturated and estimated models had an NFI value of 0.966 and 0.942, respectively, indicating a good fit as the value exceeds the threshold of 0.90 (Hu and Bentler, 1999). Therefore, the results suggest that the proposed model, which integrates signaling theory and SET, is well-suited to explain impulsive buying tendencies in LSC.
The assessment of the structural model started by evaluating the collinearity between the predictors. As shown in Table 5, the VIF values of all the combination paths were between 1.000 and 1.413 (<3.33, see Hair et al., 2020), indicating that collinearity is not at a critical level. Next, the bootstrapping technique with 10,000 subsamples was used to test the significance of the relationships between the constructs (Hair et al., 2020). Table 5 shows that streamer interaction quality (β=0.541; p<0.01) positively influenced streamer credibility, supporting H1. Besides, both streamer credibility (β=0.328; p<0.01) and streamer interaction quality (β=0.393; p<0.01) had positive relationships with product information quality, providing support for H2 and H3. Regarding the effect size ($f^2$), only the hypothesized path of H5 ($f^2=0.508$) showed a large effect. The paths hypothesized in H1 ($f^2=0.207$), H3 ($f^2=0.182$) and H4 ($f^2=0.241$) exhibited medium effects, while H2 ($f^2=0.128$) had a small effect.

Furthermore, the relationships of product information quality (β=0.569; p<0.01) to customer engagement were positive and significant, supporting H4. Finally, customer engagement (β=0.743; p<0.01) positively affected the impulsive buying tendency, hence supporting H5 (see Table 5). Overall, the proposed model explained approximately 29.2% of the variance for streamer credibility, 40.1% for product information quality, 33.8% for customer engagement, and 56.4% for impulsive buying tendency.

Next, the predictive relevance of the model was evaluated using the PLS$_{predict}$ procedure (Shmueli et al., 2019). As demonstrated in Table 5, the $Q^2_{predict}$ values for all endogenous constructs were greater than 0, indicating the model’s predictive relevance. By extending the prediction assessment, Table 6 shows that the root mean square error (RMSE) of the PLS-SEM model is lower than the RMSE in the linear model (LM), indicating the key endogenous items for the IBT have strong predictive relevance.

5.7 Mediation result

To estimate the proposed mediation role of customer engagement, this study followed the procedure recommended by Cheah et al. (2021). Table 5 showed that customer engagement (β = 0.423; p <0.01) significantly mediated the paths between product information quality and impulsive buying tendency. Thus, H6 was supported. The effect sizes of the indirect path were then calculated using the respective standardized $v$ effects and interpreted using the benchmarks of 0.01 (small), 0.09 (medium), and 0.25 (large) (Lachowicz et al., 2018). Thus, the mediation path had a medium effect ($v=0.176$, see Table 5), which signifies the important
role of customer engagement in mediating the link between product information quality and impulsive buying tendency.

5.8 Moderating result
The moderation analysis was examined by a two-stage approach (Becker et al., 2023). As exhibited in Table 5, The results indicated that guanxi orientation significantly moderated the relationships between product information quality and customer engagement ($\beta=0.105$, $p<0.05$), and customer engagement and impulsive buying tendency ($\beta=0.065$, $p<0.05$). In terms of the effect size of moderation paths, this study interpreted $f^2$ using the guidelines given by Kenny (2016): 0.005 (small), 0.01 (medium), and 0.025 (large). The findings showed that both moderation paths (H7a: $f^2=0.020$; H7b: $f^2=0.010$) had medium effect sizes, supporting H7a and H7b. The interaction plots showed that the line of high guanxi orientation had a steeper gradient than low guanxi orientation for both significant hypotheses (see Figure 2, Panels A and B). This, thus, indicates that when the customer is strong in guanxi-oriented, the positive relationships between product information quality on customer engagement, and customer engagement on impulsive buying tendency are stronger.

[Insert Figure 2 here]

6. Discussion and implications
6.1 Theoretical implications
Using both signaling theory and SET as the theoretical basis, our results supported all proposed hypotheses and suggested various fruitful implications for future research into LSC. Firstly, this research makes a significant contribution to the field of LSC by utilizing signaling theory in the complex interplay between streamers and customers in the two-way interaction process. We found that streamer interaction quality positively influences streamer credibility (H1), indicating that high streamer interaction quality enhances the relationship with customers and evidences their credibility (Gong and Li, 2019; Zhang et al., 2022). We contribute significantly to understanding the complex interplay between streamer signals by emphasizing trust-based relationships to ensure effective streamer-customer communication. Besides, we found positive influences of streamer-centered signals (streamer interaction quality and streamer credibility) on product-centered signals (product information quality) (H2 and H3), evidence that streamer quality positively and significantly impacts customers' judgments of product quality (Xue et al., 2020; Yan et al., 2022). Our findings expand the understanding of signals
in LSC beyond product-centered factors and solidify the causal relationship between streamer- and product-centered information quality. Furthermore, we found that product information quality positively affects customer engagement (H4), which, in turn, facilitates impulsive buying tendency (H5). The findings indicate that symmetric information exchange is particularly important in reducing customer uncertainty on product fit and arousing customer positive emotion, facilitating customer engagement behaviors such as liking, sharing, and commenting (Oh et al., 2017; So et al., 2021b). This implies that customers may simplify their decision-making process by heuristically processing streamer-centered information, trusting credible streamers with good interaction quality to reassure them about product information, and ultimately encouraging impulsive buying in LSC (Wang and Scheinbaum, 2018).

Secondly, this research contributes significantly to LSC by uncovering the mediating role of customer engagement in impulsive purchase decisions using SET. Our findings establish that customer engagement serves as a crucial mechanism linking product information quality to impulsive buying tendencies (H6). Existing research focuses on customer engagement as a one-way process for building customer-brand relationships (e.g., Hollebeek et al., 2021), overlooking its reciprocal nature and influence on impulsive purchase decisions. Grounding on SET, our research contributed by revealing how customer engagement serves as a reciprocal relationship mechanism, fostering a sense of obligation and a desire to conform, thus reinforcing impulsive purchase tendencies.

Lastly, the interaction analysis indicated that product information quality on customer engagement and customer engagement on impulsive buying tendency differs across the different levels of guanxi orientation (H7a and H7b). Previous studies have suggested that guanxi orientation can moderate attitudes and behaviors (Cropanzano et al., 2017; Su et al., 2021; Ding et al., 2017), and we have contributed to refining guanxi's role in social exchange and impulsive purchase decisions. Our study, supported by SET, empirically investigates how guanxi orientation facilitates the impulsive buying process among Millennial shoppers in the LSC context.

6.2 Practical implications
This study reveals the importance of streamer recommendations in positively influencing customer engagement and impulsive buying tendencies. Our results provide several practical implications for streamers in LSC platforms.

Firstly, as streamer credibility and interaction quality positively influence information quality, streamers should focus on ensuring that product information is communicated
effectively. For example, streamers need to respond to bullet-screen comments and questions promptly, address concerns openly, and create a friendly and supportive community (Zeng et al., 2023). Besides, streamers should build credibility by involving continuous learning, displaying professional knowledge, and collaborating with brand-related service personnel to enhance product selection and authenticity (Jiang et al., 2022). Additionally, streamers can boost credibility through self-disclosure during real-time interactions, shortening psychological distances with customers and strengthening relationship ties (Chung and Cho, 2017). Moreover, product information quality is important in influencing customer engagement and impulsive buying tendency. To better engage with customers, streamers need to provide believable, useful, and vivid information that matches customers’ needs (Guo and Sun, 2022). To deliver more authentic, vivid product demonstrations, streamers can show the manufacturing process of their products through LSC, enhancing customers’ trust and engagement.

Secondly, the mediation results showed that the effectiveness of information exchange on impulsive buying tendency primarily depended on the streamers’ effectiveness in engaging with customers. It is suggested that streamers provide a more engaging atmosphere to reduce 'binge-watching', as it directly and indirectly impacts customers' impulsive buying tendency. For example, streamers can remind customers of important product information before checkout, accompanied by a limited-time offer (Chen et al., 2022a), creating a sense of urgency that encourages impulsive buying. This can be achieved without creating a thrilling moment. By capitalizing on the synergy between engagement, content dynamics, and decision points, streamers can seamlessly integrate impulsive buying opportunities into the customer experience in LSC.

Lastly, the moderation results indicate that guanxi-oriented customers are more likely to engage and make purchase decisions with streamers who provide high-quality information (Dong et al., 2017; Gharib et al., 2020). The findings suggest that streamers should aim to establish a reciprocal relationship with their customers by offering financial benefits such as coupons, free gifts, and lucky draws, as well as inviting them to join the fan group (Jia et al., 2022). According to Zhang et al. (2019b), guanxi-oriented shoppers are more likely to actively engage with streamers to obtain valuable information based on the principle of reciprocity in guanxi. Additionally, Wu et al. (2021) found that guanxi-oriented shoppers are more likely to make impulsive purchases in a more engaging environment. It is important to note that this behavior is specific to guanxi-oriented shoppers. This indicates a move away from solely
informative strategies toward an emphasis on relationship-based persuasion, which could result in increased engagement and sales.

6.3 Conclusion and further research

This study, rooted in signaling theory and SET, explores the impact of streamers’ signals (interaction quality and credibility) on customers' assessment of product information quality and impulsive purchase decisions in the exchange relationship. Our findings reveal that favorable perceptions of streamer interaction quality and trust in the streamer's credibility enhance the evaluation of product information, fostering increased customer engagement and impulsive buying tendencies. Additionally, we investigate customer engagement as a mediator, reinforcing the link between product information quality and impulsive buying tendencies. The results also deepened our understanding that guanxi-oriented customers strengthen the relationships of product information quality to customer engagement and customer engagement to impulsive buying tendency.

Despite these findings, this study has several limitations. Firstly, the data collected are limited to Chinese Millennials, limiting generalizability across diverse cultures. Future research could explore cross-country variations, considering the moderation effects of guanxi orientation in collectivism vs. individualism contexts (Cakanlar and Nguyen, 2019). Secondly, this study fails to consider the possible differences between various LSC platforms. Future investigations should consider the distinct characteristics of various LSC platform types and their effects on customers’ impulse buying tendencies (Kang et al., 2020). Lastly, it should be noted that the research model did not provide an exhaustive list of all potential antecedents. To gain a deeper understanding of the significant impact of orally expressed information content by the streamer (including the various effects of discounts and the value of coupons) and the influence of negative/positive comments shared by co-viewers, future studies could conduct experimental research to dig deeper into this issue (Tóth et al., 2022).

References


Song, S., Zhao, Y.C., Yao, X., Ba, Z. and Zhu, Q. (2021), “Short video apps as a health information source: an investigation of affordances, user experience and users’ intention to continue the use of TikTok”, *Internet Research*, Vol. 31 No. 6, pp. 2120-2142.


Figure 1. Conceptual Framework

Notes: Note(s): Dashed line boxes are lower-order constructs/dimensions; EMP (Empathy); RTI (Real-Time Interaction); RES (Responsiveness); EXP (Expertise); TRU (Trustworthiness); BEL (Believability); USE (Usefulness); VIV (Vividness); AFE (Affective Engagement); BEE (Behavioral Engagement); COE (Cognitive Engagement); SOE (Social Engagement)

Source: Authors' own illustration.
Figure 2. Panel A is the interaction plot of product information quality and guanxi orientation on customer engagement, and Panel B is the interaction plot of customer engagement and guanxi orientation on impulsive buying tendency.

Source: Authors' own illustration.
Tables

Table 1: Demographic Profile

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Source: Authors' own illustration.
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Table 3: Assessment of the Discriminant Validity using HTMT

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<td>0.297</td>
<td>0.263</td>
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Note(s): HTMT<0.85 (Hair et al., 2020)
Source: Authors' own illustration.
Table 4: Assessment of Higher-Order Construct

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<th>Weights</th>
<th>T-values</th>
<th>CI</th>
<th>Convergent validity</th>
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<td>7.996**</td>
<td>[0.263; 0.433]</td>
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<td>11.29**</td>
<td>[0.400; 0.568]</td>
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<td>11.047**</td>
<td>[0.439; 0.628]</td>
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<td>7.914**</td>
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<td>0.633</td>
<td>15.405**</td>
<td>[0.550; 0.711]</td>
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<td>15.581**</td>
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<td>7.284**</td>
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Note(s): * p<0.05, ** p<0.001; VIF=Variance Inflation Factor; CI=95% confidence interval bias corrected.

Source: Authors' own illustration.
Table 5: Assessment of Structural Model

<table>
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<th>Hypothesis and relationship</th>
<th>Std beta</th>
<th>Std error</th>
<th>t-value</th>
<th>CI</th>
<th>VIF</th>
<th>$f^2$</th>
<th>$R^2$</th>
<th>$Q^2_{predict}$</th>
<th>$\nu$</th>
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<td>H1: SIQ $\rightarrow$ SC</td>
<td>0.541</td>
<td>0.039</td>
<td>13.825**</td>
<td>[0.475; 0.604]</td>
<td>1.000</td>
<td>0.207</td>
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<td>H2: SC $\rightarrow$ PIQ</td>
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<td>0.040</td>
<td>8.308**</td>
<td>[0.263; 0.392]</td>
<td>1.413</td>
<td>0.128</td>
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<td>0.401</td>
<td>0.207</td>
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<td>H3: SIQ $\rightarrow$ PIQ</td>
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<td>0.039</td>
<td>9.978**</td>
<td>[0.328; 0.457]</td>
<td>1.413</td>
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<tr>
<td>H4: PIQ $\rightarrow$ CE</td>
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<td>0.042</td>
<td>13.513**</td>
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<td>H5: CE $\rightarrow$ IBT</td>
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<td>29.319**</td>
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<td>H6: PIQ $\rightarrow$ CE $\rightarrow$ IBT</td>
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<td>0.041</td>
<td>10.412**</td>
<td>[0.351; 0.486]</td>
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<tr>
<td>H7a: PIQ *GO $\rightarrow$ CE</td>
<td>0.105</td>
<td>0.056</td>
<td>1.875*</td>
<td>[0.028; 0.184]</td>
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<td>H7b: CE*GO $\rightarrow$ IBT</td>
<td>0.065</td>
<td>0.039</td>
<td>1.667*</td>
<td>[0.004; 0.118]</td>
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<td>0.010</td>
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</tbody>
</table>

Control variable

| Education level $\rightarrow$ IBT | 0.004    | 0.024     | 0.146   | [-0.038; 0.043]  |
| Gender $\rightarrow$ IBT          | 0.011    | 0.049     | 0.216   | [-0.071; 0.091]  |
| Monthly income $\rightarrow$ IBT  | 0.004    | 0.024     | 0.154   | [-0.036; 0.045]  |
| Purchase frequency $\rightarrow$ IBT | -0.006  | 0.024    | 0.261   | [-0.043; 0.033]  |
| Usage duration $\rightarrow$ IBT  | 0.045    | 0.023     | 1.930*  | [0.006; 0.083]   |

Note(s): NA means not applicable for the situation when a single exogenous construct is used to predict an endogenous construct (Hair et al., 2020); *p < 0.05; **p < 0.01; VIF=Variance Inflation Factor; PIQ=Product Information Quality; SIQ=Streamer Interaction Quality; SC=Streamer Credibility; CE=Customer Engagement; IBT=Impulse Buying Tendency; GD=Guanxi Orientation.
Source: Authors' own illustration.
Table 6: Assessment of $\text{PLS}_{\text{predict}}$

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<th>Item</th>
<th>$Q^2_{\text{predict}}$</th>
<th>PLS-SEM_RMSE</th>
<th>LM_RMSE</th>
<th>PLS-SEM_RMSE - LM_RMSE</th>
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<td>1.410</td>
<td>-0.001</td>
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</tbody>
</table>

**Note(s):** LM = linear model; RMSE = root-mean-square error.

**Source:** Authors' own illustration.
Appendix

Appendix A: List of measurement items

**Product Information Quality (Zhang et al., 2020)**

**Believability**
- BEL1: The product information from the streamer is reliable.
- BEL2: The product information from the streamer is believable
- BEL3: The product information from the streamer is trustworthy.
- BEL4: The product information from the streamer is sincere.

**Usefulness**
- USE1: The product information from the streamer is valuable.
- USE2: The product information from the streamer is informative.
- USE3: The product information from the streamer is helpful.
- USE4: The product information from the streamer is useful.

**Vividness**
- VIV1: The product information from the streamer has stimulated my senses.
- VIV2: The product information from the streamer is clear.
- VIV3: The product information from the streamer is concrete.
- VIV4: The product information from the streamer is realistic.
- VIV5: The product information from the streamer is colorful.

**Streamer Interaction Quality (Zhang et al., 2020)**

**Empathy**
- EMP1: Streamers give me individual attention.
- EMP2: Streamers understand my specific needs.
- EMP3: Streamers had my best interests in mind.
- EMP4: Streamers offer personalized service to me.

**Real-time Interaction**
- RTI1: The interaction with streamers is real-time.
- RTI2: The real-time interaction with streamers can meet my needs.
- RTI3: The real-time interaction with streamers is efficient.

**Responsiveness**
- RES1: Streamers are always happy to talk with me.
- RES2: Streamers always answer my questions and requests promptly.
Streamers’ responses are closely related to my problems and requests.
Streamers can provide relevant information for my inquiries in time.

**Streamer Credibility (Ohanian, 1990)**

**Expertise**
- EXP1 The streamer is an expert.
- EXP2 The streamer is experienced.
- EXP3 The streamer is knowledgeable.
- EXP4 The streamer is qualified.
- EXP5 The streamer is skilled.

**Trustworthiness**
- TRU1 The streamer is dependable.
- TRU2 The streamer is honest.
- TRU3 The streamer is sincere.
- TRU4 The streamer is reliable.
- TRU5 The streamer is trustworthy.

**Customer engagement (Vivek et al., 2014; Dessart et al., 2016)**

**Affective engagement**
- AFE1 I find live-streaming shopping is interesting.
- AFE2 I am interested in anything about live-streaming shopping.
- AFE3 When interacting with people during live-streaming shopping, I feel happy.

**Behavioral engagement**
- BEE1 I share my ideas with others during live-streaming shopping.
- BEE2 I seek ideas or information from others during live-streaming shopping.
- BEE3 I am likely to recommend streamer’s live streaming to my friends.
- BEE4 I am likely to become a fan and a follower of the streamer.
- BEE5 I am likely to keep track of the activities of a streamer.

**Cognitive engagement**
- COE1 I spend more time on live-streaming shopping.
- COE2 Time flies when I am interacting with people during live-streaming shopping.

**Social engagement**
- SOE1 I like sharing my personal shopping experience with other viewers.
- SOE2 I enjoy live-streaming shopping more when I am with other viewers.
- SOE3 Live-streaming shopping is more fun when other people around me do it too.
**Guanxi Orientation (Ding et al., 2017)**

<table>
<thead>
<tr>
<th>GO1</th>
<th>Chinese society is composed of a kind of personal guanxi net.</th>
</tr>
</thead>
<tbody>
<tr>
<td>GO2</td>
<td>I enjoy the life that includes human concern and kindness.</td>
</tr>
<tr>
<td>GO3</td>
<td>Personal guanxi is an important resource in social interaction.</td>
</tr>
<tr>
<td>GO4</td>
<td>People should get on with each other harmoniously.</td>
</tr>
<tr>
<td>GO5</td>
<td>I will try to build a good relationship with others.</td>
</tr>
</tbody>
</table>

**Impulse Buying Tendency (Beatty and Ferrell, 1998)**

<table>
<thead>
<tr>
<th>IBT1</th>
<th>When I watch live-streaming, I buy things that I had not intended to purchase.</th>
</tr>
</thead>
<tbody>
<tr>
<td>IBT2</td>
<td>I am a person who makes unplanned purchases in live-streaming shopping.</td>
</tr>
<tr>
<td>IBT3</td>
<td>It is fun to buy spontaneously in live-streaming shopping.</td>
</tr>
</tbody>
</table>