



Impact of perceived diagnosticity on live streams and consumer purchase intention: streamer type, product type, and brand awareness as moderators

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Abstract

As a business innovation in the e-commerce marketplace, the use of live streams to boost sales has become an important strategy for e-tailers on major e-commerce platforms globally. However, little theoretical research has been conducted to understand the role of streamers and products in live streaming commerce. Thus, in this study, to examine consumers' perceived diagnosticity and purchase intention, we adopt a 2 (streamer type) × 2 (product type) × 2 (brand awareness) experimental design and conduct a field experiment at a university in southern China, drawing on stimulus-organism-response (SOR) theory. Our results indicate that when a product is recommended by an influential streamer during an e-commerce live stream or has high brand awareness, consumers perceive a high level of diagnosticity, which improves their purchase intention. However, we find no significant effect of product type on the perceived diagnosticity of viewers watching e-commerce live streams. We also discuss the implications of our findings for both theory and practice.

Keywords Live streaming commerce · Streamer type · Product attributes · Perceived diagnosticity · Purchase intention

1 Introduction

As live streaming becomes increasingly popular around the world, an increasing number of sellers are choosing to adopt it as a tool to improve their sales performance [59, 68]. Live streaming commerce, also referred to as live stream shopping or e-commerce live streaming in some studies, is considered a subset of e-commerce that is embedded in real-time social networking (including real-time video and text-based chat channels; [6, 69]. The uniqueness of live streaming commerce is that it provides a channel for sellers to interact and engage with online users, enabling two-way instant communication through sellers' live product

demonstrations and synchronous user interactions via a live streaming platform's functionalities [64]. Compared to traditional e-commerce, based on product images and parameters, live streaming commerce has a lower degree of information loss when delivering information to consumers. This form of high HCI puts consumers in a rich environment where live video from streamers and other user-generated content (e.g., text messages or emojis) allow consumers to receive a constant flow of rich information to support their purchase decisions. As a new way of online shopping, live streaming commerce contains not only many social commerce attributes but also unique social media attributes [6], and thus a large number of sellers are taking advantage of live streaming to generate significant opportunities in terms of marketing, customer service and revenue [46].

In March 2016, Amazon launched "Style Code Live", becoming the first U.S. e-commerce giant to venture into live streaming commerce. Sadly, Amazon canceled this service in May 2017. Although this first attempt was not successful, afterward, many traditional e-commerce companies and social networking sites began to use live streaming as an important means to broaden their online retail markets, such as AliExpress.com and Facebook. In addition, several start-ups have noted the potential of live streaming commerce,

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such as Liveby and Talkshoplive, and have invested in the industry. Despite the many interested companies, however, the integration of online shopping into live streaming is still not mainstream in the U.S. [7]. In contrast, in Asian countries, such as Thailand, Malaysia, and China, live streaming has attracted many consumers [7, 68]. Clearly, while this situation is inextricably linked to factors such as cultures and economies in different regions, during the COVID-19 pandemic, many businesses, industries, and sectors seized the opportunity presented by live streaming during lockdowns amid social and physical distancing to reach existing and new customers [1]. Worldwide, live streaming commerce thus continues to emerge as one of the mainstream online shopping methods.

Despite the growing popularity of live streaming commerce, research on it has been limited. This could be because live stream shopping is booming in China but has only just started in the U.S. [6]. According to the CNNIC [15], as of December 2020, the number of live streaming commerce users in China was 388 million, accounting for 39.2% of all internet users. Users who had purchased goods in e-commerce live streams accounted for 66.2% of all live streaming commerce users, of whom 17.8% completed more than 30% of all their online purchases during live streams. Undoubtedly, China is becoming one of the key components in the global live streaming commerce industry. Thus, as one of the world's leading e-commerce markets, China's experiences will help other countries develop live streaming commerce.

Live streaming commerce can take place through three channels: (1) live streaming platforms that incorporate commercial activities (e.g., TikTok and Liveme); (2) e-commerce sites, marketplaces (e.g., Taobao and Amazon), or mobile apps (e.g., Talkshoplive shops) that integrate live streaming features; and (3) social networking sites (SNSs) that add live streaming features (e.g., Facebook Live and Weibo Live) to facilitate sales [69]. The essential logic of live streaming commerce is simply that a product is shown to users during an e-commerce live stream, and, via the streamer's explanation, they feel the desire to purchase it. Then, through logistics delivery, consumers receive their goods, forming a closed-loop business. Some researcher have proposed researching live streaming commerce from the perspective of streamers [10], Li et al., [48] to compare the different effects of streamers who endorse their own products and those who broadcast for other brands. This study thus responds to these calls by differentiating live streaming commerce from the streamer perspective. Specifically, live commerce streamers can be classified into two main categories: online store streamers and influential streamers (Table 1). An online store streamer usually is usually the online seller himself or herself or a store employee who has a long-term employment relationship with an online seller. The main task of an online store streamer is to provide consulting

Table 1 Online store streamer vs Influential streamer

Composition		Characteristics	Strengths	Challenges	Typical representatives
Online store streamer	Online sellers themselves, online store employees, or full-time streamers hired through third-party operating companies	Online store streamer mainly provides consulting services to consumers who watch the store e-commerce live streaming show. In general, its live content revolves around the products in the online store	Streamers are usually more knowledgeable about the products sold in online stores and are less expensive to hire. Due to the existence of long-term employment relationships, the live hours of different products are guaranteed	Exposure and traffic are not high, and the conversion rate needs to be improved	Online store streamers for selling products through Facebook live (Fig. 1) and online store streamers on Taobao.com (Fig. 2)
Influential streamer	Internet celebrities (the vast majority), traditional celebrities (such as singers and film actors), entrepreneurs and government officials, etc	Usually, run live by MCN agencies, the streamer does not have a long-term employment relationship with the sellers and is often only responsible for specific products. Typically, the merchandises covered by their live content often come from several different online sellers and brands	For those Internet celebrities who are famous for recommending goods, their more experience in e-commerce live streaming can help drive up the conversion rate of live streaming. In addition, influencers tend to attract more attention and many consumers to watch	In the field of live streaming commerce, there is a Matthew effect among Internet celebrities and fierce competition among waist-tail streamers. In addition, some live viewing users watch out of curiosity and thus have little purchasing power	PewDiePie (Internet celebrity, from Youtube), Viya (internet celebrity, from Weibo), Chloe Lukasiak (actress, from Talkshoplive), and Lei Jun (president of XIAOMI, from TikTok)

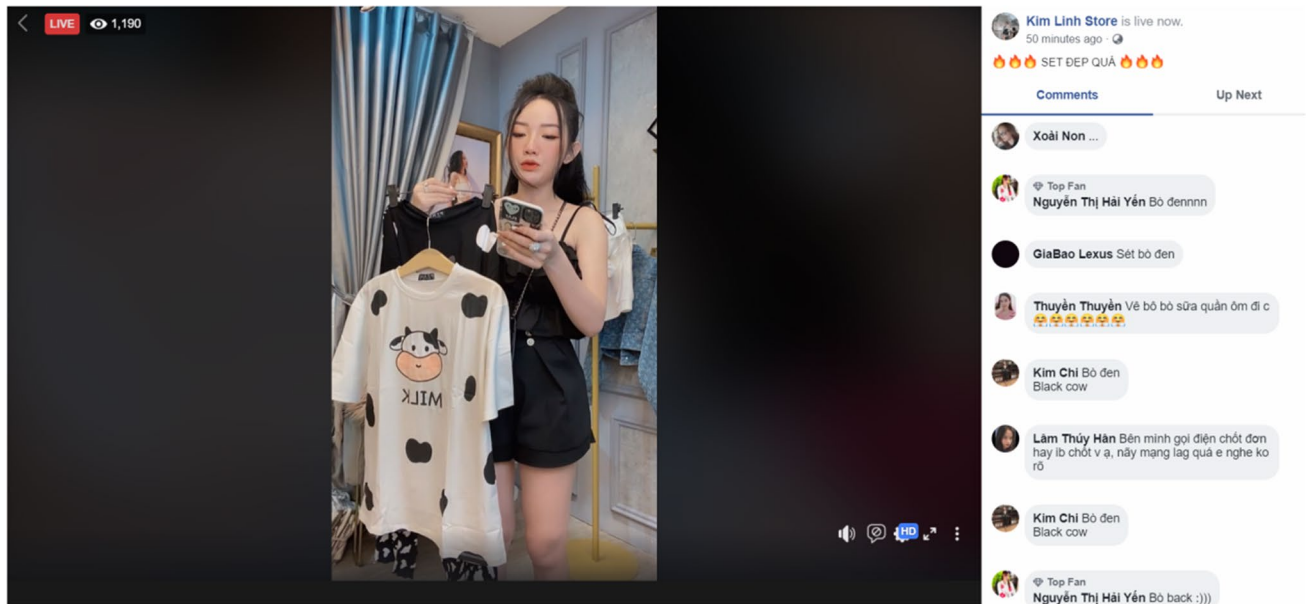


Fig. 1 An online store streamer from Southeast Asia is promoting her store's clothes on Facebook live

services to the viewers of his or her e-commerce live stream. For example, many product introduction pages on Taobao.com have shortcuts to an online store streamer (Appendix Fig. 1). Influential streamers, in contrast, are usually streamers who do not have a long-term employment relationship with an online seller, and thus most internet celebrities who are associated with e-commerce live streaming fall into this category. Compared to online store streamers, influential streamers tend to be more popular and have a larger fan base, and the contents of their e-commerce live streams often involve multiple brands of products. Hence, relative to the work of online store streamers, the relationship between influential streamers and products is often a “one-time endorsement relationship”, for example, XIAOMI is recommended by an average of 178 e-commerce streamers per day [31], while 85% of YouTube superstar PewDiePie's monthly \$8 million revenue derives from his product endorsements [62]. Notably, there are a few internet celebrities who have their own online stores and thus may be deemed both online store streamers and influential streamers, such as the famous Chinese weblebrity steamer Xueli, whose store on Taobao.com, “Mrs. Qian's Home—Xueli Custom (Clothing Store)”, has over 20 million followers. She also provides live streams for a variety of other brands' products, such as Panasonic's kitchenware, Hollywood's snacks, and FanBeauty Secret's skin care products.

In addition, as the live streaming commerce literature is still in its infancy, the role played by product attributes in e-commerce live streams has not been fully studied. Previous research on e-commerce has shown that when consumers pay attention to different product types, such as search

goods or experience goods, there are differences in their online product information search attitudes and behaviors [30, 65]. While [74] and Chen et al. [13] suggest that experience products may be more appropriate for live streaming commerce scenarios than search products, their studies do not distinguish between the types of streamers or various product attributes in live stream shopping. Accordingly, a deeper discussion of the role that product type plays in live streaming commerce is necessary. In addition, Smith and Wheeler [58] argue that high brand awareness increases people's trust in a brand and its advertising. Hence, in the field of social commerce, brand awareness has been the focus of scholarly discussions [3, 17, 22]. Therefore, as live streaming is both a useful marketing communication tool and an important source of reference for consumers in their purchase decision process [68], understanding how streamer type and product attribute (e.g., product type or brand awareness) affect consumers' perceived diagnosticity is critical to understanding how live stream shopping affects consumers' psychological processes. Finally, this study also examines the effect of consumers' perceived diagnosticity on their purchase intention. Accordingly, in this study, we aim to address the following research questions:

RQ1: Is there a difference in consumers' perceived diagnosticity when the same product is live streamed by an online store streamer or an influential streamer?

RQ2: What role do product attributes play in live streaming commerce?

RQ3: Does a consumer's perceived diagnosticity have a positive effect on his or her purchase intention?



Fig. 2 An online store streamer from China is selling snacks on Taobao.com

To address these research questions, we performed a field experiment at a university in southern China. We examined the effects of streamer type, product type, and brand awareness on consumers' perceived diagnosticity. The relation between consumers' perceived diagnosticity and their purchase intention in live streaming commerce is also explored in our study's model. Moreover, we used a 2 (streamer type) \times 2 (product type) \times 2 (brand awareness) experimental

design to test our hypotheses. A covariate, prior transaction experience, was also included in our stimulus to control for unexpected variation between the variables. Regarding our results, we conclude this study by presenting their theoretical and managerial implications for academics and marketers.

2 Literature review and hypotheses

2.1 Live streaming commerce

Live streaming commerce refers to a subset of e-commerce that uses live streams for real-time social interactions to facilitate shopping [6]. Live streaming employs one or more communication technologies that allow images and sounds to be sent instantly to other locations, thus allowing users to perceive a telepresence [8]. Hence, live streaming commerce includes many social commerce attributes and unique social media attributes, for example, synchronization, authenticity, and entertainment [5, 25]. As live streaming overcomes the asynchronous nature of traditional social commerce, an increasing number of platforms and sellers have joined the live streaming commerce bandwagon, for example, Amazon, Facebook, and Instagram have all added "live stream shopping" features to their platforms.

In terms of research purposes, the literature mainly discusses the antecedents of consumer purchase intention and participation in the context of live streaming commerce [1, 7, 10, 64, 68, 75]. In addition, some studies discuss live streaming commerce from the perspective of sustainable development [14], streamer-product fit [53], or supply chains [33]. With respect to research methodology, empirical studies based on data from online questionnaires, i.e., consumer self-reports, remain dominant [24, 28, 59]. In addition, a few scholars have adopted a qualitative research method; for example, Wongkitrungrueng et al. [69] have studied the live streaming strategies of online sellers, and Lu et al. [46] have explored the value judgments of consumers. Notably, some scholars performing empirical studies have recently chosen to collect data from live streaming platforms [12, 34], using experimental designs to observe the actual behavior of users [20, 74].

Although such studies have deepened our understanding of live streaming commerce, they have notably either investigated only one type of user or have not differentiated between users. Therefore, it is imperative to compare the behavior of different types of live stream shoppers [28]. Accordingly, our differentiates users by distinguishing between the types of streamers and then comparing their behavior. In addition, rather limited research has considered product attributes when evaluating live streaming as an emerging online shopping method. Therefore, we explore the mechanisms by which streamer type and product attribute

(product type and brand awareness) influence consumers' online shopping process in the context of live streaming commerce.

2.2 SOR model

The SOR model posits that environmental and informational cues act as stimuli that affect an individual's cognitive and affective reactions, which, in turn, affect his or her behavioral intentions [49]. Stimuli (S) may appear in different formats [32]. Many previous studies have demonstrated that product information and its source are important stimuli in the online purchase process [47, 54, 63, 76]. Therefore, we use streamer types and product attributes in live streaming commerce as our stimuli (S). Organism (O) refers to an individual's cognitive systems, conceptualized in the SOR model as an internal individual evaluation when interacting with a stimulus [18]. Perceived diagnosticity is defined as the extent to which consumers consider particular aspects of their shopping experiences to help them evaluate products [36]. The concept of perceived diagnosticity has been widely used in social media and online shopping-related research [11, 23]. Product attributes and information sources may have varying degrees of influence on consumers' perceived diagnosticity [51, 63]. For marketers, helping consumers evaluate products is an important goal that affects their purchasing process [63]. Therefore, we introduce the concept of perceived diagnosticity into the research context of live streaming commerce as the organism (O) in our SOR model. Response (R) represents psychological reactions, e.g., attitudinal, or behavioral reactions. Because actual behavior is difficult to measure, it is common to measure behavioral intentions instead, as intentions have been shown to be effective predictors of actual behavior [61]. Hence, we define a consumer's purchase intention toward a product recommended by a streamer as the response (R) in our SOR model.

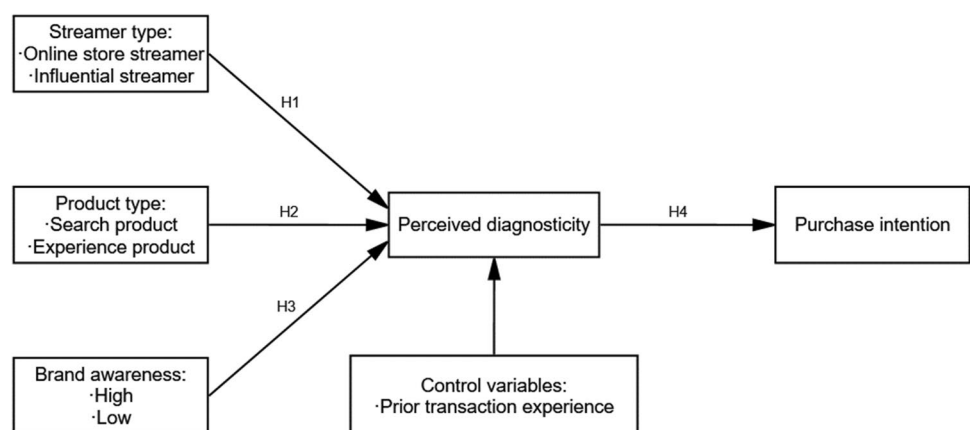
For several reasons, it is appropriate to use the SOR model as the overall framework for this study. First, Cai and

Wohn [6] argue that live streaming commerce is a subset of e-commerce that uses live streams for real-time socialization to facilitate shopping. Therefore, evaluating live streaming commerce from the perspective of social media and e-commerce allows us to follow existing studies. The SOR model has also been widely used in previous studies related to social commerce. For example, Zhang et al. [73] use the SOR model to investigate the determinants that motivate customers to engage in social commerce, and Hu, Huang, Zhong, Davison, and Zhao [29] apply the SOR model to reveal the impact of the peer characteristics and technological features of social shopping sites on consumers' purchase intentions. Second, regarding the key role of the influence of information and cognition on consumer behavior in live streaming commerce, the SOR model provides a simple and structured way to examine the impact of information sources and product attributes—as stimuli on consumers' perceived diagnosticity—and, consequently, their intention to purchase a product that is recommended by a streamer (Fig. 3).

2.3 Streamer type

Streamer type in this study is defined by the relationship of a streamer with a product and seller. Although it is difficult to determine streamer type due to the incomplete information of most streamers engaging in live streaming commerce, in general, we identify them as either online store streamers or influential streamers to simplify this classification. Simply put, an online store streamer is responsible for an entire store or brand, while an influential streamer is generally responsible for specific products. For example, an online store streamer in the Nike store on Taobao.com needs to be on duty to answer live viewers' questions about all of the Nike brand's products, e.g., clothes, shoes, or hats. An influential streamer, however, may agree with Nike to broadcast a new Nike sneaker in an e-commerce live stream only on a certain day, and Nike will pay the influential streamer a commission or offer him or her a sales commission. In general, the

Fig. 3 Theoretical framework



many and varied products covered in the e-commerce live streams of influential streamers come from different brands; thus, they may be pushing high-calorie snacks 1 min and diet tea the next. A simple way to determine whether an e-commerce live streamer is an online store streamer or an influential streamer is to observe the title of the stream. When a streamer is an online store streamer, the title of an e-commerce live stream generally includes the store or brand name (Appendix Fig. 2); when a streamer is influential, the title of his or her e-commerce live stream will generally include the streamer's name or the topic of the stream's content rather than a specific brand or product title (Appendix, Fig. 3).

Moreover, online store streamers are mostly marketers who are hired by sellers, or they are the sellers themselves; hence, 90% of the live content on Taobao.com is self-broadcast by online sellers [35]. Facebook Live has also actively followed Taobao.com's live streaming commerce model since the global outbreak of COVID-19 to help small business owners promote their products and services online [43]. The composition of influential streamers is rather complex, including professional streamers, internet celebrities, self-media streamers, traditional celebrities, entrepreneurs, and even government agencies, although the most well-known and influential streamers who engage in e-commerce live streaming are mostly internet celebrities [60].

On the one hand, compared to online store streamers, influential streamers generally have higher popularity or greater expertise in a certain area, which attracts users to watch their e-commerce live streams [53]. Compared to online store streamers, who broadcast live streams on e-commerce sites, a user is only more likely to find and watch an e-commerce live stream by an internet celebrity or other type of influential streamer if the user follows the information of the latter [42]. On the other hand, most of the influential streamers are also users of the target products [56], and making a name for themselves by successfully portraying themselves as experts on social media platforms [37]. They also tend to uphold their reputation regarding recommending products and are less likely to choose ordinary quality products that will tarnish their reputation. Therefore, compared to those of online shop streamers, who have a direct interest for or as sellers, the product recommendations of influential streamers are more likely to be perceived as acceptable by users [2, 38].

In addition, numerous studies related to social commerce confirm that promotion by social media celebrities positively influences users' purchasing behavior [21, 66, 71]. That is, consumers are more likely to remain positive if they know that the streamer in an e-commerce live stream is an influencer. According to experience economy theory, the more positive the product experience that is gained through experiential interaction, the more likely consumers are to believe

they have received detailed product information [55]. Thus, we hypothesize the following:

H1 Compared to online store streamers, influential streamers make consumers perceive a higher degree of diagnosticity.

2.4 Product type

In the field of e-commerce, some studies have classified products into search or experience products based on their characteristics [4, 40, 50]. Some examples of search products include cameras, cell phones, and computers, which are characterized by the objectivity of their key product attributes, making them easy to compare, and they are easy to obtain [30, 51]. In contrast, the evaluation of experience goods, such as video games and travel destinations [65], can be highly subjective [50], with personal taste playing an important role.

In traditional e-commerce, the stable attributes of search products are better suited to the online shopping environment than those of experiential products [48]. The emergence of live streaming commerce, however, seems to have changed this situation to some extent. Zhang et al. [74] have shown that the influence of a live video streaming (LVS) strategy on perceived uncertainty is stronger for experience products than search products. Chen et al. [12] have found that live streaming plays a more efficient role in convincing online users to purchase experience goods, demonstrating that the adoption of a live streaming strategy by shops that mainly sell experience goods increases their sales by 27.9% more than the use of a similar strategy by retailers of products that are mainly search goods. During the traditional online transaction process, it is more difficult to evaluate the characteristics of experience products with their product specifications before purchase than for search products [57]. However, e-commerce live streaming allows viewers to observe a real image of an e-retailer [59] and to access visual and auditory information that is difficult to convey via pictures and text. In contrast, the information provided by streamers in e-commerce live streams does not provide much additional value or enjoyment when consumers are looking for the search product. Hence, task-media fit theory suggests that higher levels of visual information do not always improve consumer learning [48]. When consumers look for a search product, they focus on the product itself, not personal context or environment. While live streaming can provide value to a search product, as consumers may also want to gain insight into the appearance of a search product through a streamer's product presentation, the contextual information from a live stream does not have much influence on such a purchase decision [13]. Thus, for experience goods, real-time interaction via live streaming can

largely reduce perceived uncertainty, but for search goods, this effect is likely attenuated [74]. Therefore, we hypothesize the following:

H2 The information presented in the e-commerce live stream of an experience product has a greater positive impact on perceived diagnosticity than that of a search product.

3 Methodology

This study examines the influence of streamer type, product type, brand awareness, and perceived diagnosticity on consumer purchase intention. To evaluate our hypotheses, we designed a 2 (streamer type) \times 2 (product type) \times 2 (brand awareness) stimulus. We conducted pretests before the formal experiment to design stimulus materials for manipulating the variables. We designed eight scenarios to measure consumers' perceived diagnosticity and purchase intention for products that are recommended in e-commerce live streams.

3.1 Stimulus material

Streamer type design: A key aspect of our research is to compare online store streamers with influential streamers. Unlike an online store streamer, a user is more likely to reach and watch a live streaming shopping show from an Internet celebrity or other type of influential streamer only if he follows the information of those people. To give a sense of immersion to most subjects with the live streaming shopping experience, we chose widely known celebrities as representatives of influential streamers, such as Viya [16] and Benny Sa [67]. Streamers of online stores on Taobao.com are considered as online store streamers in this study.

Product selection: To select a representative experience/search product for the experiment, 35 graduate students from a university in southern China participated in a pretest. We selected six products (smartwatch, Bluetooth headset, desk lamp, toast bread, denim jacket, shoes) that are not unfamiliar to college students in their daily lives and are frequently found in other related studies, all of which appeal to respondents to some degree and are easy to obtain and purchase. We used the 3 questions of Moon et al. [50] to measure product type. The responses were measured on a seven-point Likert scale with 1 = 'Do not agree at all' and 7 = 'Agree.' This phase refers to Zhang et al. [74] for the research design of selecting experience products and search products in the context of live streaming commerce. Specifically, Bluetooth headset (Mean = 4.257) had the highest average score for the three questions and toast bread (Mean = 3.129) had the lowest average score, so we chose

Bluetooth headset as our search product and toast bread as our experience product.

Brand selection: We first selected 10 real brands for Bluetooth headsets and 10 real brands for toast bread from Taobao.com based on sales volume and e-commerce to live streaming data. Taobao.com is considered the largest e-commerce platform in China, where more than half of Chinese consumers' online shopping activity is done. Further, 20 brand names presented in a list and two questions developed by Laurent, Kapferer, and Roussel [39] were used to measure brand awareness. 50 college students were asked to indicate their ability to identify and recall these brands using a Likert-style 7-point scale (from 1 (Do not agree at all) to 7 (Agree completely)). If the combined average of the two questions about a particular brand is high, then brand awareness is high; otherwise, brand awareness is low [47]. Finally, four brands were selected based on the extremes of the combined mean scores. The search product with high brand awareness was Huawei (MeanQ1 + Q2 = 7.47), while the search product with low brand awareness was JBL (MeanQ1 + Q2 = 3.21). In terms of experience products, the experience product with high brand awareness came from Three Squirrels (MeanQ1 + Q2 = 8.45), and the experience product with low brand awareness came from Honyifood (MeanQ1 + Q2 = 3.45).

3.2 Experimental design

Based on the above discussion, the authors designed 2 (Streamer type: online store streamer or influential streamer) \times 2 (product type: search product or experience product) \times 2 (brand awareness: high or low) stimulus and recorded 8 Chinese versions of live streaming shopping scenarios. All recording was done on the same mobile device. It is worth pointing out that the prices of similar products from different brands often vary and one type of product of a brand often has multiple specifications. For example, there are dozens of models of Bluetooth headsets of Huawei and JBL. Therefore, we have selected the Bluetooth headset models with similar product positioning (e.g., in-ear headset, noise-canceling, and long battery life) and the smallest price difference. Detailed grouping information can be found in Appendix Table 4.

It is worth noting that when watching e-commerce live streaming shows on cell phones, consumers can choose to show or turn off social cues (i.e., herding message and interaction text) by simply tapping any blank space on the screen to toggle the feature on or off. According to the selective attention theory, Fei et al. [20] divide the attention of users who watch e-commerce live streaming shows into endogenous attention and exogenous attention. In the context of live streaming commerce, consumers' attention to products and streamers should be regarded as

endogenous, and social cues should be regarded as exogenous. Fei et al. [20] showed that endogenous attention is positively related to purchase intention, while the effect of exogenous attention is relatively more complex, involving the competing mechanisms of the distracting effect and social influence. Based on the above discussion and following the purpose of this study, we chose to hide the social cues in the e-commerce live streaming show during recording to prevent the presence of social cues from interfering with the results of the influence of streamer type and product attributes on consumers' perceived diagnosticity.

Before recording product recommendations for the online store streamer, we first observed the behavior of 10 volunteers in the live store room of a product, recorded the questions most likely to be asked by consumers, and asked these questions by an additional device during the formal recording. The explanation for this is that online store streamers are more like traditional salespeople and it is their job to present more information about the products to consumers. Usually only when consumers consult with online store streamers, they will explain the specific product live. For influential streamers, especially popular Internet celebrities, are less likely to notice individual consumer problems and less likely to interact with individual viewers [12]. Online store streamers often repeatedly introduce the same product to different audiences, while the relationship between influential streamers and products is like a "one-time endorsement relationship", and they rarely introduce the same product to audiences repeatedly due to the fixed length of a single e-commerce live streaming show and the inflexible order of product appearances.

To control for other possible distractions, we also controlled the video content, ensuring that all eight videos contained the same important content, such as sampling snacks and showing product details. After these 8 scenes were designed, we invited 10 Chinese graduate students to examine the recording of each scene to check for possible confusion effects and other problems in the actual experiment. Respondents were asked to view an experimental live video and complete a final questionnaire. We received feedback and suggestions from the respondents after they completed the initial testing. Overall, all respondents felt that the experimental procedures were conducted successfully.

3.3 Measurement

The 3-items scales of Wang and Chang [63] were used to measure perceived diagnosticity and the 3-items scales of Zeithaml et al. [72] were used to measure purchase intention and modified these items to fit the context of our study. The questionnaire was answered on a seven-point Likert scale

ranging from "strongly disagree" to "strongly agree". The questionnaire items are listed in full in Appendix 3.

3.4 Participants and procedures

These subjects were recruited from a university in southern China, and they all had some prior transaction experience about live streaming commerce. We prepared a fruit salad for each subject and provided a chance to draw a prize to show our appreciation. A total of 416 subjects with extensive online shopping experience (i.e., more than one online purchase per month) participated in this experiment, and they were randomly assigned to 8 groups, i.e., 52 subjects in each group.

After participants were randomly assigned to eight experimental groups, we asked each group of subjects to imagine a scenario to fit the realistic context. For example, one group of subjects was told that their best friend had a birthday coming up and that they needed to pick up a pair of Bluetooth headsets from an electronics retailer as a gift for him/her. The purchase was presented as a gift to reduce the possibility of the low relevance between the category and non-Bluetooth headsets-wearing participants. We sent the corresponding product link (copy the link to open the product page directly in the mobile Taobao.com APP) and the live video to the subjects' own mobile devices, and then officially started the experiment. We first let them browse the product information freely and then watch the corresponding live video. Finally, we distributed a post-experimental questionnaire, as well as a recall test of the details of the stimulus video. The entire experiment lasted approximately 15 min per subject.

To ensure that the respondents' responses were authentic and reliable, data from 18 subjects were excluded from the data analysis because they did not pass the information recall test or give the same answers throughout the experiment. As such, the data analysis was completed with data from 398 validated subjects (221 females, 177 males; mean age = 23.21).

3.5 Reliability

Cronbach's α and item-to-total correlation of each scale were examined to ensure an acceptable level of internal consistency. The Cronbach's α of each construct (0.922 for perceived diagnosticity and 0.931 for purchase intention) exceeds 0.7, which is considered adequate for our analysis [52].

4 Data analysis and results

4.1 Manipulation checks

Several items were used to check the operational definitions of streamer type, product type, and brand awareness. First, subjects were asked, "Do you think the streamer in the e-commerce live streaming show is a full-time streamer employed by XXX online store on Taobao.com?" This is a 0–1 scale to check the operation of the streamer type. Subjects' responses were similar to our operational definition, and only a very small number of subjects incorrectly differentiated streamer types, indicating that our manipulation of streamer types was successful. Second, for the product type manipulation check, subjects were asked to rate three questions developed by Moon et al. [50], scoring a 7-point Likert scale. Bluetooth headsets and toast were rated differently on each of the three items of the product type operation. The findings of the *t*-test indicated that the mean score of Bluetooth headset (Sample size = 201) is higher than the mean score of toast (Sample size = 197) (MeanBluetooth headset = 4.31, MeanToast = 3.25, *P*-Value = 0.000), which indicates that our product type operation is successful. Finally, subjects were asked to rate two questions on brand awareness developed by Laurent et al. [39], and to rate each item on a Likert-style 7-point scale ranging from 1 (strongly disagree) to 7 (strongly agree). *T*-test results showed that live streaming recommendations with high brand awareness scored significantly higher than live streaming recommendations with low brand awareness (MeanHigh = 3.74, MeanLow = 2.16, sample sizeHigh = 198, sample sizeLow = 200, *p*-value = 0.000). The results show that the operation of brand awareness was also successful.

4.2 Hypotheses testing

ANCOVA analysis: To control for factors that may lead to unexpected variation among variables, this study included a covariate, prior transaction experience, as a control variable in the testing model to remove the external influences from the dependent variable. Consumers' online shopping behavior is influenced by their past online shopping experiences [70]. E-commerce live streaming as a form of online shopping, consumers are more likely to have a positive attitude toward accepting the product information provided by the streamer in the e-commerce live streaming show when they consider their previous live streaming shopping experience to be satisfactory. This study suggests that prior transaction experience could improve consumers' perceived diagnosticity in live streaming shopping, as they are more likely to trust the streamer and the content about the product in the

live streaming. The 3-item scale of Prior transaction experience developed by Chen et al. [10] was used to measure by a 7-point Likert-type scale, ranging from 1 (strongly disagree) to 7 (strongly agree). Therefore, because the covariate of prior transaction experience was a metric independent variable, the design is then termed analysis of covariance (ANCOVA) design to test hypotheses 1, 2, and 3 [47].

Before conducting the ANCOVA analysis, we first performed a parallelism test to see if there was an interaction between the independent variables and the covariate. The results showed that there was no interaction between the three independent variables and the covariate of the model. In addition, we performed Levene's Test of equality of error variances, which was significant at 0.255, which is greater than 0.05, and therefore concluded that the error variance of the dependent variable is equal across groups. The above test results can be viewed in Appendix Table 2 and 3. Table 2 shows the results of the ANCOVA analysis. Streamer type has a significant effect on perceived diagnosticity ($F(1,389) = 27.925, p\text{-value} < 0.001$). If the streamer is influential (MeanInfluential streamer = 4.77), the consumers' perceived diagnosticity will be more positive than the online store streamer (MeanOnline store streamer = 4.17). This result supports H1. Whether the product in the e-commerce live streaming show is a search product (MeanSearch = 4.41) or an experience good (MeanExperience = 4.53), consumers' perceived diagnosticity is unaffected ($F(1, 389) = 1.841, p\text{-value} > 0.05$). Thus, H2 is not supported. Finally, consumers' perceived diagnosticity is also significantly influenced by brand awareness ($F(1, 389) = 14.318, p\text{-value} < 0.001$).

Table 2 ANCOVA results

Source	df	Mean square	F	Sig
Corrected model	8	15.936	11.389	0.000
Prior transaction experience	1	62.54	44.693	0.000
Streamer type(A)	1	39.075	27.925	0.000
Product type(B)	1	2.576	1.841	0.176
Brand awareness(C)	1	20.036	14.318	0.000
A × B	1	1.394	0.996	0.319
A × C	1	0.032	0.023	0.879
B × C	1	0.107	0.077	0.782
A × B × C	1	0.527	0.377	0.540
Error	389	1.399		
Total	398			

Dependent variable: Perceived diagnosticity

Correlation and regression analysis: Because there is only one independent variable, this study tests hypothesis 4 using bivariate correlation analysis. Based on the findings in Table 3, the relationship between perceived diagnosticity and purchase intention is positively significant (correlation coefficient = 0.637, *p*-value < 0.001). This result is in line with the regression analysis ($\beta = 0.637, t\text{-value} = 16.431, p\text{-value} < 0.001$).

Table 3 Results of Pearson correlation and regression analysis

Pearson correlation	Perceived diagnosticity		Purchase intention
Perceived diagnosticity	1		
Purchase intention	.637**		1
Model	Standardized beta	Standard error	t-Value
Regression analysis			
Perceived diagnosticity	0.637	0.043	16.431**
F-Value = 269.968** R ² = 0.405			
Dependent variable: Purchase intention			

** p -Value < 0.001

Consumers will have a higher level of acceptance of the information about the product delivered by the streamer in the e-commerce live streaming show if the product recommended by the streamer has higher brand awareness (Mean-High = 4.72). The lower the brand awareness, the lower the consumers' perceived diagnosticity of the product (Mean-Low = 4.23). Therefore, H3 is supported by the results of this study.

5 Conclusion

Live streaming commerce allows streamers to interact with users by introducing and displaying products in real time, which in turn activates their consumption intention and thus improves purchase rates and user experiences. Since live streaming is increasingly considered an effective marketing tool by a growing number of e-commerce sellers, it is important to examine the perceived diagnosticity of consumers in the context of live streaming commerce. Therefore, we conducted a 2 (Streamer type) × 2 (Product type) × 2 (Brand awareness) experimental design via the control variables of prior transaction experience. A valid sample of 398 subjects was used to examine consumers' perceived diagnosticity and purchase intention in the context of live streaming commerce.

First, based on the ANCOVA results, there is a significant relationship between streamer type and perceived diagnosticity, the focus of H1. If the streamer in an e-commerce live stream is an influential streamer with high popularity, a consumer's perceived diagnosticity will be higher than when the streamer is an online store streamer. This result is consistent with previous studies related to the type of streamer and the necessary supplements that have been completed. As live streams can provide a more effective environment for celebrity-fan interactions than traditional mass media, many consumers perceive their user-based contents to be more trustworthy than traditional commercial strategies [53]. While Geng et al. [21] have shown that endorsements

by weblebrities lead to increased user visits and sales for e-commerce sellers, this study elaborates on this phenomenon via the perspective of perceived diagnosticity. Specifically, we find that when a consumer intends to purchase a product online, a recommendation from an influencer will give the consumer extra confidence to choose that product. Furthermore, this study extends the findings of Cai et al. [7], which suggest that only hedonic motivations (i.e., physical attractiveness and interest in a streamer) significantly predict celebrity-related scenarios in the context of live streaming commerce. Our results indicate that consumers' interest in influential streamers is likely based on the latter's provision of convincing product information, that is, on their higher degree of perceived diagnosticity.

Notably, it is found that product type has no significant effect on consumers' perceived diagnosticity, which shows that H2 is not supported. This differs from the findings of [9], which suggest that live streaming plays a more effective role in persuading consumers to purchase experience goods. One possible reason for this is that the data in Chen et al. [9] was derived from Taobao.com's product sales data, whereas the data for our study came from consumers' self-perceptions. Clearly, the characteristics of a search product entail that it is more stable, more objective, and easier to evaluate than an experience product [27]. Accordingly although an experience product may be more suitable for the live streaming environment, a live stream can only reduce the relative difficulty of accessing information regarding an experience or search product, it cannot achieve overtake. For example, if the information provided by a traditional shopping site allows consumers to perceive an 8-point diagnostic level for search products and a 5-point diagnostic level for experience products, but the advent of live streaming allows consumers to perceive an additional 2-point diagnostic level for search products and an additional 5-point diagnostic level for experience products, then "8 + 2" = "5 + 5". However, the opposite is not true, which should be sufficiently exciting for online sellers who mainly sell experience products. In addition, our findings support H3, which suggests that

consumers' perceived diagnosticity is influenced by brand awareness. If consumers have high brand awareness of the product recommended in an e-commerce live stream, their perceived diagnosticity of that product will increase. Brand awareness thus helps increase consumers' confidence and their perceived level of product information, which is consistent with previous research findings [45, 47]. Brands play an important role in reducing the perceived risk of purchase [26]. Thus, consumers are more likely to believe the claims of a streamer when they have high brand awareness.

Finally, this study has also examined the effect of perceived diagnosticity on purchase intention (H4). Our results show that perceived diagnosticity is a powerful element in explaining purchase intention in the context of live streaming commerce. If consumers perceive the diagnosticity of the positive information that they receive about a product to be high, then their purchase intentions will be high. This finding that perceived diagnosticity directly influences purchase intention supports the findings of Wang & Chang [63] and Fang [19]. Accordingly, a credible e-commerce live stream should positively affect consumers' willingness to purchase its products [10, 75].

6 Implications

In this study, we have developed a model to investigate the underlying mechanisms of consumer decision-making in the context of e-commerce live streaming, making several theoretical contributions to the fields of live streaming commerce and online marketing communication. We provide empirical evidence that shows how streamer type, brand awareness, and perceived diagnosticity play an important role in the decision to apply live stream recommendations.

This study therefore makes the following theoretical contributions: First, we follow the initiative of existing research, that is, we research live streaming commerce from the perspective of the streamer [10, 41]. For this purpose, we have used an experimental design to collect data to explore the effect of streamer type on consumers' perceived diagnosticity. Second, prior research on live streaming commerce has not adequately examined product attributes. Hence, we identify product type and brand awareness as antecedents of consumers' perceived diagnosticity in our research framework to determine what elements improve consumers' perceived diagnosticity for goods recommended by streamers in e-commerce live streams. These findings have shaped our preliminary understanding of consumers' perceptions of live stream shopping when evaluating a product before purchase. Third, our study introduces the concept of perceived diagnosticity into the context of live streaming commerce, which is a powerful element for explaining purchase intention. Finally, previous empirical studies of live streaming

commerce have typically used self-report surveys [44, 59], but data based on consumer recall are likely to cause biased findings that make it difficult to quantitatively examine the impact of live content on consumer purchase intentions. Accordingly, we have collected real-time data from live stream shopping users in an experimental design that simulates a real environment, providing a new method for better measuring consumers' actual responses and opinions.

The results of this study could also be used to help develop guidelines for more effective marketing strategies, as e-commerce sellers need to use live streaming recommendations to broaden their marketing channels and increase product sales. First, this study shows that consumers feel a higher degree of perceived diagnosticity when the streamer in an e-commerce live stream is an influencer. Influential streamers can therefore help online retailers improve their image and gain the trust of more users. In addition, studies have proven that endorsements of influential streamers increase product or brand exposure, which in turn attracts more consumers and makes them more likely to make impulse purchases [21]. Thus, second, our results suggest that although the effect of product type on perceived diagnosticity is not significant, given the findings in numerous previous studies regarding the inappropriateness of experience products for the traditional e-commerce environment, sellers who primarily sell experience products online should take advantage of live streaming to improve consumers' perceived diagnosticity and thereby increase their product sales. Finally, the power of a brand is still reflected in the context of live streaming commerce. Higher brand awareness therefore entails that consumers are more likely to trust the information about a given brand's product in a live stream. This reiterates the importance that companies and manufacturers should provide to branding. Furthermore, it implies that e-commerce live streamers, especially those who are only minor celebrities, must carefully select the items they recommend to avoid losing the trust of their followers and viewers.

7 Limitations and suggestions for future research

This study has several limitations. First, to ensure the quality of the study data, a convenience sample was used, while the respondents were undergraduate and graduate students at a university in southern China. The generalization of our findings is thus limited because the survey samples were all from China. Future research should expand the sample profile by using random sampling and cross-cultural comparison. Studying the effects of age, occupation, education, and culture on the perceived diagnosticity of subjects would further improve the understanding of live streaming

commerce. Second, regarding streamer type, we selected influential streamers that are well known to the public. Many influential streamers are, however, little known; they may not be that famous, but they often have a very loyal and strong purchasing fan base. Future research should therefore be more segmented in terms of streamer type; for example, influential streamers can be divided into different tiers according to their influence. In addition, we should consider more niche types of streamers, who may be both influential streamers and online store streamers (e.g., Xueli, a web-lebrity who opened her store on Taobao.com) or may not be either influential or online store streamers (such as the recently emerged AI virtual streamer). Third, since all four brands used in the experiments exist in real life, consumers' prior experience with these brands may have influenced the results of this study. Finally, in this study, we have excluded the interference of social cues because our focus is on consumers' endogenous attention, i.e., consumers' attention to streamer and product(s). However, influential streamers' e-commerce live streams may have a higher degree of social cues, which in turn attracts consumers' exogenous attention. Nevertheless, the effect of exogenous attention is relatively more complex, involving the competing mechanisms of the distracting effect and social influence [20]. Future experimental designs should thus take social cues into account, along with supporting instruments, such as eye-tracking, to investigate how and why consumers' perceived diagnosticity or purchase intention changes in different situations where such social cues are activated or neutralized.

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