What Should Streamers Communicate in Livestream E-Commerce? The Effects of Social Interactions on Live Streaming Performance

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Abstract

Compared with traditional e-commerce, livestreaming e-commerce is characterized by direct and intimate communication between streamers and consumers that stimulates instant social interactions. This study focuses on streamers' three types of information exchange (i.e., product information, social conversation, and social solicitation) and examines their roles in driving both short-term and long-term livestreaming performance (i.e., sales and customer base growth). We find that the informational role of product information (nonpromotional and promotional) is beneficial not only to sales performance, but also to the growth of the customer base. We also find that social conversation has a relationship-building effect that positively impacts both sales and customer base growth, whereas social solicitation has both a relationship-building and a relationship-straining effect that positively affects customer base growth but can hurt sales. Furthermore, our results show that streamers' social interactions with consumers can stimulate consumer engagement in different ways, leading to different effects on livestreaming performance.

Keywords: E-commerce livestreaming, influencer marketing, social conversation, social solicitation, product information, consumer engagement

Introduction

In the past few years, e-commerce platforms have shifted from using text- and image-centric content to video-oriented content to promote sales, thanks to the advancement of internet technologies. Appeared in 2016, livestream e-commerce has experienced an explosive growth. Livestream shopping represents a new form of e-commerce that incorporates live video content, two-way communication between streamers and viewers, and the ability for viewers to seamlessly buy featured products directly from the platform. The value of China's livestream e-commerce market has surpassed one trillion RMB in 2020 and is estimated to reach 35 billion dollars in the U.S. by 2024.[1] Many e-commerce platforms such as Amazon and Taobao have launched livestreaming functions, and the livestream e-commerce is expected to maintain a high growth rate on these platforms in the next few years. Despite such great promises, streamers experience different levels of success in this new arena (Wongkitrungrueng et al., 2020). There is still very limited empirical research to understand what drives the performance and success of livestream e-commerce.

E-commerce livestreaming combines influencer marketing with instant shopping (Bharadwaj et al., 2022), which is a form of social commerce by leveraging the role of influencers (streamers, in the context of e-commerce livestreaming) in impacting consumers' preferences and purchase decisions (Karagür et al., 2022). Social interactions and commercial functions are two main features of livestreaming e-commerce. Different internet platforms are moving towards the integration of social and commercial attributes from two directions: social media platforms such as Facebook and Instagram are introducing commercial features that allow advertising and transactions; traditional e-commerce platforms such as Amazon and Taobao are adding social functions to enable social interactions (Zhang & Benyoucef, 2016).

In addition to immediate sales performance, another goal of livestreaming e-commerce is to build a larger follower base for long-term benefits (Leung et al., 2022). Although the growth of the follower base may not immediately impact current-period sales performance, it reflects the potential for future sales and thus an important indicator of long-term benefits. Therefore, these dual goals are pursued simultaneously. However, because traditional e-commerce has focused primarily on consumer market demand for products, little insight is known about the long-term goal of livestreaming e-commerce.

Factors influencing the two goals may be different (Wang et al., 2020). Consumers make purchase decisions mainly based on the assessment of product attributes, while they decide whether to follow an influencer based on the interactive content features beyond product information (Bapna et al., 2019). On the one hand, some product information can directly drive consumers' path to purchase conversion but may not be effective in follower acquisition. On the other hand, some influencers' social conversations with consumers may be beneficial in attracting followers, but they may not help to increase purchase intentions. In addition, influencers frequently and explicitly solicit viewers to follow their accounts to attract new followers and increase their customer base. Such solicitation may result in resistance from some consumers, leading to immediate loss of sales and even hurting consumers' following intentions (Pogacar et al., 2018). Thus, there is a need to understand the different key factors that contribute to each goal and the trade-offs involved in balancing the two goals.

Traditionally, influencers rely on texts, images, or short videos for their marketing campaigns (Leung et al., 2022). They attempt to provide high-quality content to obtain good marketing performance. Although social media helps their social interactions with consumers, limited by the content creation mode, all published content is pre-produced, and the social interactions are neither instant nor frequent. Unlike traditional forms of influencer marketing, e-commerce livestreaming provides an unprecedented opportunity for streamers to directly interact with consumers using real-time communication via video streaming (Lin et al., 2021), which enables streamers to build immediate interpersonal relationships with consumers and even make social solicitations to consumers in addition to introducing products. Analyzing instant communication between streamers and consumers can provide important insights into the effective information that drives livestreaming performance.

Apart from the streamer side, consumers are also an integral part in the communication relationship. Following previous research, we focus on consumer engagement, which is defined as the intensity of consumers' participation in and connection with the organization's offerings and/or organizational

[1] https://www.statista.com/topics/8752/livestream-commerce

activities (Bar-Gill & Reichman, 2021). Typically, there are three types of consumer engagement in response to marketer-generated content, namely likes, comments, and shares (Lee et al., 2018; Yang et al., 2019). Most prior studies show that consumer engagement is positively associated with subsequent follower base growth and online consumption behavior (Bapna et al., 2019; Gong et al., 2017; Rishika et al., 2013).

Unlike the traditional influencer marketing context in which consumer engagement and purchase take place on separate platforms (for example, consumers might "like" a photo on Instagram and subsequently buy the related product on Amazon), these activities are integrated in the same session under the new e-commerce livestreaming context. As such, the effect of consumer engagement on sales performance could be different. Since consumer engagement is stimulated by streamers who initiate and lead the communication in livestreaming, it is vital to study the effects of different types of information exchange from streamers on consumer engagement and, in turn, on product sales and customer base growth.

Hence, our research aims at investigating the effects of various types of information exchange on e-commerce livestreaming in terms of both short-term performance (i.e., sales) and long-term performance (i.e., customer base growth). More specifically, do different types of streamers' information exchange have different effects on short-term and long-term performance? And how do they affect livestreaming performance, by directly influencing sales and customer base growth, or indirectly through consumer engagement?

Motivated by the dual roles of social and commercial functions in livestream e-commerce, we examine streamers' information exchange with consumers by focusing on the commercial product information and social interactions. We further differentiate social interactions in two dimensions: social conversation and social solicitation. More specifically, product information refers to the mentioning of products and facts about products such as brand and product features (Resnik & Stern, 1977; Abernethy & Franke, 1996; Lee et al., 2018). We define social conversation as the conversations for establishing or maintaining a social relationship, such as greetings, intimate appellations to consumers and other friend-like talks, without calls to action, while social solicitation explicitly requests specific actions streamers want their viewers to take (e.g., asking viewers to like and share the livestream, leave comments, and follow the livestreaming channel) (Lee et al., 2018). The effect of product information on sales performance has been widely examined across different contexts such as firm posts on social media platforms (e.g., Mu et al., 2022), consumer reviews on e-commerce platforms (e.g., Archak et al., 2011), and TV ads (e.g., Tsai & Honka, 2021). However, the social dimension of communication, a unique feature in livestreaming and other forms of influencer marketing, is underexplored in prior studies and thus is an important contribution of this research.

Using a unique livestreaming dataset collected from a leading e-commerce platform, we estimate a panel vector autoregression (PVAR) model on the sampled livestream sessions to handle the challenge that multiple key variables related to information exchange coevolve in a dynamic system (Lin et al., 2021; Wang et al., 2021). We find that the informational role of product information (nonpromotional and promotional) is beneficial not only to sales performance, but also to the growth of the customer base. Regarding social interactions, we find a relationship-building effect of social conversation, but both a relationship-building and a relationship-straining effect of social solicitation. Social conversation and social solicitation have positive effects on the growth of the customer base, but their effects differ in sales performance. While social conversation has a positive effect on sales, social solicitation can hurt sales. Additionally, our results show that the number of comments, which can be stimulated by social interactions, positively impacts both sales and customer base growth. The number of likes positively affects customer base growth, while the number of shares negatively affects sales, implying a crowding out effect.

Our study contributes not only to the growing body of livestream e-commerce research, but also to the literature on influencer marketing. First, our work contributes to the literature investigating the information contained in influencer-generated content. In addition to providing novel insights about the effect of product information, we reveal the roles of social conversation and social solicitation in driving both short-term and long-term performance. Second, this study contributes to the research on consumer engagement by systematically examining the effects of different types of consumer engagement in the context of e-commerce livestreaming. Third, unlike most studies that examine the final marketing outcomes, our analysis examines the dynamic process of livestreaming to capture the dynamic and interactive nature of this business context and to disentangle both the direct and indirect effects of streamers' information exchange. These findings also have valuable practical implications for streamers and platforms to improve e-commerce livestreaming performance.

Related Literature

Influencer Marketing

Influencer marketing is widely adopted in social commerce by utilizing influencers' role in affecting consumers' preferences and purchase decisions (Karagür et al., 2022). Most prior studies in influencer marketing are conducted in non-commercial settings such as social media platforms like Twitter and video platforms like TikTok (e.g., Hughes et al., 2019; Hung et al., 2022). Traditional e-commerce platforms are also striving to embrace the power of influencers in their commercial selling (e.g., Amazon Influencer Program). However, the integration of influencer marketing into e-commerce platforms is an emerging new phenomenon.

Recent studies have investigated how influencer marketing affects consumers' attitudes and behaviors. The focus so far has been on the information features and influencer characteristics. Product information is found to be the major type of information being delivered to consumers in influencer marketing. Gong et al. (2017) examined the informativeness of content describing the product and found that the more informative the content being disseminated, the more effective influencer marketing is. Mu et al. (2022) classified product information into different types, namely utilitarian and hedonic product information. They showed that hedonic product information has a higher positive impact on sales than utilitarian product information on social media platforms. In addition to the information itself, there are also studies examining the effect of how the information is conveyed, such as information valence or emotion (e.g., Gerrath & Usrey, 2021; Uribe et al., 2016). In terms of influencer characteristics, expertise, trustworthiness, attractiveness, personas, and similarity to the followers are some of the characteristics that can effectively distinguish influencers and impact marketing performance (e. g., Karagür et al., 2022; Lou & Yuan, 2019). Despite the sociability of influencer marketing, very few studies have investigated influencers' social interactions with consumers. As an exception, Hung et al. (2022) investigated the use of intimate addresses by influencers on video platforms like TikTok. They showed positive effect of intimate addressing on consumer engagement, but no effect on driving sales. However, intimate addressing is only one type of social conversation and our study takes other forms of social conversation as well as social solicitation into account.

In terms of marketing outcomes, most field studies in influencer marketing are interested in consumer engagement on social media platforms, including likes, comments, and shares (e.g., Rooderkerk & Pauwels, 2016; Lambrecht et al., 2018). Because the data required for the analysis of e-commerce platforms are not widely available to researchers, studies examining actual product sales are relatively scant (Mu et al., 2022). However, factors influencing consumers' engagement decisions, such as whether to like, comment, or share, can be different from those that influence their purchase decisions. The former is mainly based on the evaluation of content features while the latter is mainly based on the assessment of product features. For instance, Lee et al. (2018) found that social media posts that only contain product information such as mentions of price and deals are associated with lower levels of engagement, but such information drives consumers' path to conversion (via improved click-throughs). Hung et al (2022) also suggested that on video platforms, a product-focus content strategy can hurt consumer likes and shares (which does not seem to hold true on e-commerce platforms that are inherently product-oriented), and an engagement-focus content strategy may decrease sales. Therefore, more research is needed to investigate how influencer-generated content impacts sales performance, especially on e-commerce platforms.

Apart from sales performance, customer acquisition is also an important objective of influencer marketing. When an influencer conducts marketing activities, one goal is to build a larger customer base in the long run (Trusov et al., 2009). On social media platforms like Facebook, firms and influencers often aggressively acquire followers by investing in paid ads for broader reach of their content on the platform (Lee et al., 2018). However, few studies have taken the customer base growth into consideration, which is a long-term performance measure (Gong et al., 2017).

Livestreaming

Livestreaming, as a new channel that enables content creators to deliver their content to viewers in real time, has become a popular model of influencer marketing, in which streamers (influencers) play a crucial role (Kang et al., 2021). Different from other forms of influencer marketing where influencers publish pre-produced content such as articles and short videos, streamers continuously generate content in a livestream session. Meanwhile, viewers watch and consume the content and also engage with streamers in various ways that can help shape the content generation process (Lin et al., 2021).

This study focuses on e-commerce livestreaming. E-commerce livestreaming features streamers hosting live selling events as they interact with the audience, thereby monetizing in ways not possible previously (Bharadwaj et al., 2022). Unlike other types of livestreaming, e-commerce livestreaming is product-driven, which primarily serves to sell products (He et al., 2021). Different from the traditional influencer marketing context where consumers engage on social media platforms and buy on e-commerce platforms, e-commerce livestreaming integrates these activities together and shortens the purchase journey. As such, the relationships between consumer engagement and sales performance may differ.

Existing research on livestreaming indicates that social interaction is an important factor driving consumers' participation. For example, Sjöblom and Hamari (2017) and Diwanji et al. (2020) suggested that social motivations are the main reasons for viewers to watch and engage in livestreaming in addition to information needs. Ang et al. (2018) and Hilvert-Bruce et al. (2018) emphasized the importance of real-time interaction between streamers and viewers. In livestreaming, streamers can interact with consumers in different ways. Extant research has suggested the importance of appeal strategy leveraging a personal tone, such as intimate addressing, to make the influencer approachable and create a public intimacy (Marshall, 2014; Hung et al., 2022). Another type of social interaction is through solicitation, which explicitly solicits consumers to comment, like, share, or follow, thereby providing an explicit option to foster engagement (Lee et al., 2018). The unique bidirectional feature of livestreaming implies a context in which social solicitation can be effective, since it is resided within the flow of natural conversation, but as a type of imperative statement requesting action, social solicitation may also lead to counterproductive outcomes because of its propensity to induce resistance from message recipients (Pogacar et al., 2018). Thus, the effect of social solicitation in livestream e-commerce remains unclear.

Only recently, an emerging body of research shifts the focus to the economics of livestreaming (e.g., Chen et al., 2020; Lu et al., 2021). Chen et al. (2020) suggested that after sellers adopted livestreaming, the average increase of sales volume is 6.18% per product. In addition to overall product sales, recent research has investigated the role of specific streamer-generated content in driving sales within a livestream session. Guo et al. (2021) examined the effect of streamers' social interaction on sales performance in e-commerce livestreaming, but they do not differentiate social conversation from social solicitation. Since social solicitation specifically focuses on consumer engagement rather than short-term sales, these two factors can influence the dual goals of e-commerce livestreaming differently. Hung et al. (2022) showed that in short videos, influencers' use of intimate addresses has a positive effect on consumer engagement, but no significant effect on sales. Hence, there is also a need to study whether and how streamers' social interaction affects sales and customer base growth differently.

In the highly interactive livestreaming context, social interaction (especially social solicitation) in influencer marketing is of particular importance, but it is an underexplored area of research. Additionally, prior studies either focus only on product sales or consumer engagement metrics (e.g., comments, likes, or shares), but not both. The dual goals of influencer marketing should be systematically examined. Our research aims to fill this research gap by examining the effects of streamers' product information exchange and social interactions with consumers on driving livestream sales performance and the growth of customer base.

Research Framework and Hypotheses

Research Framework

Because of the highly interactive relationship between streamers and consumers and the highly integrative nature of the social and commercial aspects of e-commerce livestreaming, we first build a systematic framework to describe the relationships between the relevant parties (i.e., streamers and consumers) and livestreaming performance. Due to the commerciality and sociability of e-commerce livestreaming (Kang et al., 2021), we examine both the sales of each livestream session and the growth of customer base, as short-term and long-term performance measures.

We focus on three types of information exchange from streamers: product information, social conversation, and social solicitation. We further divide product information into promotional and nonpromotional (Tsai & Honka, 2021). Although there are other ways to categorize product information, we choose this perspective because finding great deals and learning more about product features have been suggested as two main reasons why consumers watch e-commerce livestreaming[1]. Promotional product information contains product price and any type of discounts and freebies, while nonpromotional product information informs other characteristics of the product such as brand, color, size, and functionality. These are illustrated on the left side (i.e., streamers' information exchange) of our framework, as shown in Figure 1.

A unique feature of livestreaming is that consumers can interact with streamers in real time. Previous research suggests that marketer-generated content can influence sales indirectly by stimulating other user-generated content (Song et al., 2019). Accordingly, the level of consumer engagement can play an active role in driving livestreaming performance through real-time interaction with streamers. Following the existing literature (Lee et al., 2018; Yang et al., 2019), we measure consumer engagement using the number of likes, comments, and shares. These are illustrated in the middle part (i.e., consumer engagement) of Figure 1. Similar to Hewett et al. (2016) and Wang et al. (2021), we also control for feedback effects (denoted by dashed arrows in Figure 1) among streamers, consumers, and performance to fully capture the dynamics involved in livestreaming.

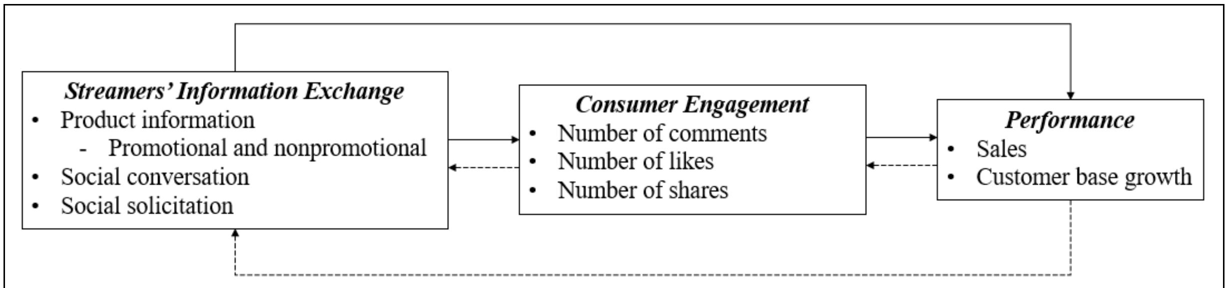

Figure 1. Research Framework

Hypothesis Development

Product Information. Product information informs consumers of product attributes and therefore raises awareness and knowledge of the product. In line with the marketing literature, we refer to this as the informational role (e.g., Mehta et al., 2008) of e-commerce livestreaming. Previous research has shown that streamers' efforts in introducing product information can increase consumers' favorable evaluations of products and drive purchases (Guo et al., 2021). Accordingly, we propose the following hypothesis.

H1. In e-commerce livestreaming, product information (nonpromotional and promotional) positively affects sales.

Promotional product information can be considered as a form of monetary incentive, which has been identified as a key driver of online community growth. Bapna et al. (2019) show that conveying promotions or offers in firm posts is associated with subsequent growth in online community size. Hence, we believe that promotional product information has a positive effect on the growth of the customer base in e-commerce livestreaming. In addition, previous research suggests that the informativeness of company tweets introducing nonpromotional product information is positively associated with the number of newly subscribed company followers (Gong et al., 2017). Because e-commerce livestreaming is inherently product-oriented (He et al., 2021), we also expect that nonpromotional product information positively affects customer base growth. Together, we hypothesize the following.

H2. In e-commerce livestreaming, product information (nonpromotional and promotional) positively affects customer base growth.

Social Conversation. In addition to sharing product information, e-commerce livestreaming encompasses processes through which streamers establish and maintain social relationships with consumers. This is called the relationship-building effect (e.g., Khazanchi et al., 2018). Lack of trust in online environments has long been identified as one of the greatest challenges faced by online sellers (e.g., Kim et al., 2009). The interpersonal relationship between consumers and sellers has been shown to build trust and increase consumers' purchase intentions (Ou et al., 2014). Therefore, we believe that streamers' social conversation with consumers contributes to such relationship building and serves as a crucial driving factor to facilitate consumer purchase. We hypothesize the following.

H3. In e-commerce livestreaming, social conversation positively affects sales.

Porter and Donthu (2008) suggest that trust motivates consumers to behave relationally toward the firm (such as granting loyalty to the firm) in online communities. Therefore, in addition to facilitating sales, we expect that streamers' social conversation that contributes to cultivating trust positively impacts consumers' following behavior in the context of e-commerce livestreaming, which can also be considered as an online community. Therefore, we hypothesize the following.

H4. In e-commerce livestreaming, social conversation positively affects customer base growth.

Social Solicitation. Social solicitation is a special type of social interaction that appears widely in livestreaming but has received little attention in previous research. The effects of social solicitation on sales can be twofold. On the one hand, it can have a relationship-building effect. Although social solicitation does not aim at boosting product sales, it can indirectly influence sales by stimulating higher consumer engagement (Rishika et al., 2013). As a result, social solicitation can have a positive effect on sales. On the other hand, a potential risk of social solicitation, as a type of imperative statement requesting actions, is its tendency to induce reactance in consumers (Pogacar et al., 2018) because consumers may feel that they are being commanded or ordered, which threatens their sense of autonomy and freedom (Brehm, 1966). In this regard, explicit social solicitation can also lead to a relationship-straining effect, referring to processes that hinder the development and maintenance of positive relationships and/or help the formation of negative relationships (e.g., Khazanchi et al., 2018), and therefore result in consumers' reluctance to purchase. We note that the relationship-building and relationship-straining effects of social solicitation on sales may coexist. Thus, we have the following two hypotheses.

H5a. In e-commerce livestreaming, social solicitation positively affects sales.

H5b. In e-commerce livestreaming, social solicitation negatively affects sales.

Similar to sales performance, the effects of social solicitation on customer base growth can be mixed. On the one hand, social solicitation can have a relationship-building effect. It can directly drive consumers to follow the streamer, thereby helping to expand the customer base. In addition, it can stimulate consumer engagement, which in turn will indirectly improve follower count (Bapna et al., 2019). On the other hand, social solicitation can have a relationship-straining effect. In the same vein as its potential negative effect on sales, social solicitation may result in resistance from consumers, thus hurting consumers' following intentions. Hence, we propose the following two hypotheses.

H6a. In e-commerce livestreaming, social solicitation positively affects customer base growth.

H6b. In e-commerce livestreaming, social solicitation negatively affects customer base growth.

Data

Research Context

To empirically answer the research questions, we obtained a unique field dataset from Taobao, one of the leading e-commerce platforms in the world. Our dataset contains livestreams of women's apparel, which is the largest category in e-commerce livestreaming. We first collect all livestream sessions of women's apparel on Taobao from March 15, 2021 to March 28, 2021. This period does not include any shopping festivals on Taobao. To ensure that our sample is representative, we remove the sessions whose time length is shorter than 0.58 hours (bottom 10%) or longer than 13.97 hours (top 10%). As a livestream session can contain multiple products, there is often more than one product category in a session. Specifically, we treat livestream sessions in which women's apparel products account for 70% or more of the total products as the sessions of women's apparel after consulting the operational staff.[2] To ease the burden of conducting

[2] Our main results are robust with respect to this category cutoff point, such as 75% and 80%.

huge volume of content analysis, we randomly select 820 sessions that started between 8pm and 10pm over the two-week period. We choose this two-hour sampling time window since both streamers and viewers are most active after 8pm on livestreaming platforms, and thus lots of streamers begin their sessions during the time period from 8pm to 10pm, which is of primary interest to livestreaming platforms (Lin et al., 2021).

Variables and Measurement

We construct our dynamic panel data by slicing each of the 820 sessions at three-minute intervals[3], resulting in 56,849 observations. For every three minutes in each livestream session, we assemble structured data such as sales volume, the number of new followers, the number of comments, likes, and shares. We also employ content analysis to analyze the audio transcripts of streamers and construct moment-to-moment measures of various types of information exchange, which we will detail below. The final data used for empirical analysis have an unbalanced panel structure, in which cross-sectional units are livestream sessions and longitudinal units are time in three minutes. The imbalance is due to the varying durations of different sessions. Next, we discuss the process of constructing variables from the unstructured data as well as the structured data.

To construct moment-to-moment measures for streamers' information exchange, we first transformed live videos into text transcripts. In this study, we resort to a state-of-the-art deep learning approach provided by Alibaba Cloud speech recognition service, which has the highest Chinese recognition accuracy in the industry.[4] We manually verified a random sample of transcribed text to ensure that they are consistent with the corresponding video set. Next, we segmented these texts before further processing, since a well-known problem with Chinese text analysis is that Chinese words are concatenated to each other in a sentence. Specifically, we utilized a word segmenter provided by AliNLP, which is tailored for e-commerce content.

Nonpromotional Product Information. Based on the above data pre-processing, we measure nonpromotional product information as the number of words conveying information relevant to the nonpromotional product features, divided by the total number of words. To operationalize this construct, we choose specific words belonging to eight categories, including brand, series, color, size, dimension, functionality (e.g., "sun-protective," "thermal"), modifier (e.g., "elastic," "skin-friendly"), and links (corresponding to product placement in a physical store). To implement this construct on a large-scale sample of texts, we employed the named entity recognition (NER) technique provided by AliNLP, which is particularly developed to analyze e-commerce content, to identify and extract specific words belonging to the first seven categories except links[5]. NER is an information extraction task that aims to locate and categorize atomic elements in text into pre-defined categories. In addition to common categories such as person names and organizations, AliNLP named entity recognizer can also extract specific categories in the e-commerce domain, including brand, color, size, etc. The named entity recognizer in AliNLP has two main advantages. First, it takes the context of a word into account, not just a single word, because the same word may have different categories in different contexts. Second, the words in each category are updated daily, and therefore it keeps up with the times to capture new things (such as new brands) and fancy usage of words.

Promotional Product Information. We measure promotional product information as the number of words delivering any kind of promotion-related messages such as discounts, coupons, and red packets, scaled by the total number of words. Specifically, we utilized the NER provided by AliNLP to extract words in the category of promotion and freebie, such as "20% off," "sec-killing," and "discount." Besides, we include words like "red packet," "coupon," "price," "lottery," and "full reduction" (e.g., buy $100.00 to save $10.00) which are not contained in the NER's category of promotion and freebie, but are also promotion-related, especially in the context of e-commerce livestreaming.

[3] Our main results are robust when we use six-minute intervals.

[4] https://help.aliyun.com/document_detail/212727.html (in Chinese)

[5] For the "links" category, we take the raw count of the word "link" minus the number of occurrences of the phrase "launch a new link." In e-commerce livestreaming, there are two approaches to release product links. The first approach, adopted by the vast majority of streamers, posts all links at the beginning of a session. The second approach, however, is to post links one by one during the entire session. In this way, when issuing a new product link, streamers always say "3, 2, 1, launch a new link," which has become a prototype. Since the word "link" no longer represents the position of the product in this case, we subtract the number of occurrences of this phrase from the total number of "link."

Social Conversation. To construct measure of social conversation, we leverage the Simplified Chinese version of Linguistic Inquiry and Word Count (LIWC). According to the percentage of words belonging to predefined dictionaries, LIWC calculates the prevalence of different categories of words in a text document (Pennebaker et al., 2015). In this study, we focus on the "social" measurement in LIWC, which indicates streamers' efforts to build social relationships with consumers (Guo et al., 2021). Examples of words in the social dictionary include "dear," "friend," "joking," "welcome," "love," etc. [6]

Social Solicitation. We construct a lexicon of terms that are likely to be used by streamers when they ask for specific social responses. In particular, this study focuses on comments, likes, shares and follows, which are most often solicited during livestream sessions. To this end, we manually mined hundreds of slices that are randomly selected from all the livestream sessions and extracted terms relevant to streamers' social solicitation. Additionally, we include their synonyms and synonymous phrases that may appear in online settings. Examples for social solicitation are terms like "send a comment," "click on like," "share the livestreaming room," and "do not forget to follow." We count the number of social solicitations in the three minutes, scaled by the total number of words.

Consumer Engagement. Apart from the aforementioned content variables from the streamers, we also measure engagement activities of the consumers. In particular, we count the number of likes, comments, and shares per three minutes of each livestream session and take the logarithm of each consumer engagement variable (plus one to avoid creating nonsense data).

Livestreaming Performance. We examine both short-term livestreaming performance (i.e., sales) and long-term livestreaming performance (i.e., customer base growth). The former is measured by the number of product units sold during the livestream session and the latter is measured by the number of new followers the livestreaming channel acquires. Again, these two metrics are log-transformed and aggregated at the three-minute level. We note that there is also the possibility of unfollowing. However, the unfollowing behavior is quite rare in our livestreaming dataset, and we found only one unfollowing behavior. Therefore, our results are robust when we measure the customer base growth as the number of new followers minus the number of unfollowers.

Table 1 provides the descriptive statistics for these variables across all three minutes of all livestream sessions. We remove the data from the last period of each session because they are always less than three minutes.

	Variable	Mean	S.D.	Min	Max
Streamers' information exchange	*NonPromoInfo*	0.0420	0.0202	0	0.1765
	PromoInfo	0.0058	0.0069	0	0.0722
	SocialConversation	0.0524	0.0264	0	0.2571
	SocialSolicitation	0.0015	0.0037	0	0.0792
Consumer engagement	*NumComments*	1.7513	1.2670	0	10.4433
	NumLikes	1.4412	1.7972	0	12.2293
	NumShares	0.1500	0.4018	0	7.2971
Performance	*Sales*	0.3231	0.6688	0	7.1709
	NewFollowers	0.2169	0.4433	0	5.1475

Table 1. Descriptive Statistics

Methodology

In an interactive and dynamic environment like livestreaming, multiple key variables coevolve together. To examine the effect of one variable on another, we must take all interactions among the variables that affect each other into account, rather than investigating each relationship individually. Following Lin et al. (2021), we use a panel vector autoregressive (PVAR) model to capture the dynamic and interdependent nature of

[6] In addition to LIWC, we utilized TextMind (Gao et al., 2013), a text analysis tool specifically for Simplified Chinese. The word categories in TextMind are compatible with LIWC. Moreover, thousands of Simplified Chinese words frequently used in microblogs are incorporated into TextMind, making it suitable for analyzing text in social media and social commerce. The results using TextMind are qualitatively the same as those using LIWC.

variables in the livestreaming and to uncover both the direct and indirect effects of one variable on other variables (Song et al., 2019). The PVAR model enables the inference of bidirectional relationships among endogenous variables and ensures robustness to issues of serial correlation, non-stationarity, endogeneity, reverse causality, and spurious causality (Granger & Newbold, 1986), and has been widely used in online contexts such as social media and livestreaming (e.g., Chen et al., 2015; Foerderer et al., 2021).

In the PVAR model, each endogenous variable is a function of its own past values and the past values of all other endogenous variables as well as exogenous variables. We specify the model as follows:

$$\begin{pmatrix} Sales_{i,t} \\ NewFollowers_{i,t} \\ NonPromoInfo_{i,t} \\ PromoInfo_{i,t} \\ SocialConversation_{i,t} \\ SocialSolicitation_{i,t} \\ NumComments_{i,t} \\ NumLikes_{i,t} \\ NumShares_{i,t} \end{pmatrix} = \sum_{s=1}^{p} \Phi_s \begin{pmatrix} Sales_{i,t-s} \\ NewFollowers_{i,t-s} \\ NonPromoInfo_{i,t-s} \\ PromoInfo_{i,t-s} \\ SocialConversation_{i,t-s} \\ SocialSolicitation_{i,t-s} \\ NumComments_{i,t-s} \\ NumLikes_{i,t-s} \\ NumShares_{i,t-s} \end{pmatrix} + \delta NewLink_{i,t} + \beta Phase_{i,t} + f_i + \varepsilon_{i,t}, \tag{1}$$

where Φ_s is a 9×9 matrix of coefficients for the s-period lagged endogenous variables, and p indicates the number of lags. To capture the new link launching effects in a few sessions where not all product links are released at the beginning, we include $NewLink_{i,t}$ to represent the number of new product links released by stream i in period t, which is measured by the number of times the streamer says "launch a new link." To control for the time trend, we introduce $Phase_{i,t}$ to indicate which phase the period t falls in the session i. In particular, we divide each session into four parts evenly and $Phase_{i,t}$ = {1, 2, 3, 4}.[7] Besides, we control for observed and unobserved session heterogeneity with session fixed effects f_i, which also alleviates the need for streamer-level fixed effects, to identify the effects of various types of information exchange based on within-session variation across time. Finally, $\varepsilon_{i,t}$ is a vector of the idiosyncratic error terms that satisfies the white noise assumption.

For PVAR analysis, the endogenous variables should be stationary. Given that our panel data are unbalanced, we performed Im-Pesaran-Shin and Fisher-type unit root tests. The results of both tests indicate that there is no unit root problem in our data. In addition, we conducted Granger causality tests to empirically investigate whether the dependent variables in Equation (1) are endogenous. The test results clearly reveal that most variables in our context Granger-cause each other. Moreover, we used the moment and model selection criteria developed by Andrews and Lu (2001) for GMM estimation to determine the optimal lag length (i.e., the p parameter) and we selected one lag for our model.

Results

Table 2 shows the main results of our model. For ease of exposition and to focus our discussion on key variables of interest, we only present the estimation results for five dependent variables here.

Effects on Sales

We first examine the short-term sales performance to understand how product information, social conversation and social solicitation from streamers affect the overall product sales in the current livestream. In the *Sales* equation, our results show that both promotional and nonpromotional product information have positive effects on sales of e-commerce livestreaming, which supports H1 and validates the informational role of product information on sales.

Regarding social interactions, we find that social conversation plays a significant role in driving sales. In addition to the direct positive effect, social conversation indirectly boosts sales by stimulating more real-

[7] Our main results are robust when we introduce more than 4 phases (e.g., 5 phases and 6 phases). Note that period dummies are not appropriate due to the differences across livestreaming sessions (Lin et al., 2021).

time comments. Therefore, H3 is supported. Our results show that the relationship-building effect of social conversation is beneficial for sales.

	Dependent variable				
Independent variable	$Sales_{i,t}$	$New\ Followers_{i,t}$	$Num\ Comments_{i,t}$	$NumLikes_{i,t}$	$NumShares_{i,t}$
$Sales_{i,t-1}$	0.1251*** (0.0247)	0.0237** (0.0090)	-0.0139 (0.0265)	0.0970*** (0.0187)	0.0501*** (0.0116)
$NewFollowers_{i,t-1}$	0.0260 (0.0235)	0.0968*** (0.0188)	-0.0003 (0.0241)	0.0591* (0.0248)	0.0462*** (0.0129)
$NonPromoInfo_{i,t-1}$	2.0000*** (0.3165)	0.3947 (0.2140)	-0.0266 (0.4646)	1.8041* (0.7539)	-0.2016 (0.1550)
$PromoInfo_{i,t-1}$	1.4027* (0.5791)	1.5324** (0.5065)	2.2003 (1.1614)	2.7663 (1.7180)	0.5514 (0.3393)
$SocialConversation_{i,t-1}$	1.0826*** (0.2559)	0.1549 (0.1710)	1.1457* (0.4469)	0.6249 (0.6724)	-0.1177 (0.1444)
$SocialSolicitation_{i,t-1}$	-3.1021** (1.0187)	1.6944* (0.7764)	6.6410** (2.5121)	9.9867** (3.3818)	0.8377 (0.6509)
$NumComments_{i,t-1}$	0.0551*** (0.0098)	0.0236*** (0.0054)	0.4534*** (0.0155)	0.1648*** (0.0164)	0.0411*** (0.0069)
$NumLikes_{i,t-1}$	-0.0054 (0.0034)	0.0042* (0.0019)	0.0219*** (0.0048)	0.4128*** (0.0132)	0.0246*** (0.0022)
$NumShares_{i,t-1}$	-0.0899** (0.0328)	0.0097 (0.0105)	0.0108 (0.0237)	0.0200 (0.0238)	0.1898*** (0.0259)
Control variables	Yes	Yes	Yes	Yes	Yes

Table 2. Main Estimation Results of the PVAR Model

Notes. The number of observations is 55,209. We use Helmert transformation to remove livestream fixed effects before conducting GMM estimation. Robust standard errors (clustered on livestream) are shown in parentheses. This table reports the estimation results for five dependent variables for brevity.
$^{***}p<0.001$, $^{**}p<0.01$, $^{*}p<0.05$.

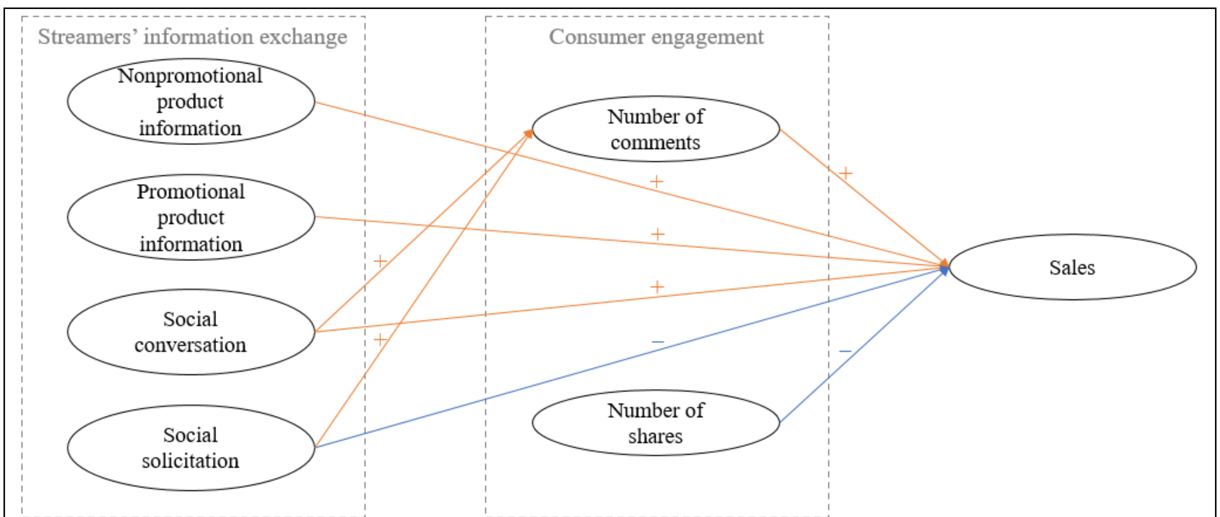

Figure 2. Main Results on Sales

Although social solicitation can also indirectly drive sales by stimulating more instant comments, the results show that it directly inhibits sales. Hence, both H5a and H5b are supported. There are both relationship-building and relationship-straining effects of social solicitation on sales performance, albeit through different routes.

These findings show that in terms of consumer engagement, the number of real-time comments plays a significant role in driving sales. Streamers' social interactions lead to more instant comments, which in turn increases product sales. Nevertheless, not all kinds of consumer engagement are conducive to sales (at least in the short term). The number of shares negatively affects livestreaming sales, which seems counterintuitive. On social media platforms, firms and influencers care about sharing per se and often invest in social media marketing for generating virality (Tellis et al., 2019). Sharing indicates endorsement from consumers, as consumers are willing to post the shared content in their social networks rather than just liking or commenting within the original community (Yang et al., 2021). However, sharing can crowd out the motivation of purchasing, leading to a crowding-out effect (Osterloh and Frey 2000). Previous research documented that engaging in an initial act of token support (such as sharing) for a cause will result in a decreased propensity to subsequently devote more substantial contributions (such as purchasing) to the cause (Kristofferson et al., 2014). Different from the traditional influencer marketing context in which consumer sharing and purchasing take place on separate platforms (typically sharing on social media platforms and purchasing on e-commerce platforms), in the context of e-commerce livestreaming, consumers share livestreams and buy products in the same livestream session, which can lead to a higher likelihood of the crowding out effect. Figure 2 visually summarizes our results on sales.

Effects on the Growth of Customer Base

We next examine how product information, social conversation and social solicitation from streamers affect the long-term livestreaming performance (i.e., customer base growth). Table 2 and Figure 3 summarize the key results. We observe that streamers introducing promotional product information can acquire more potential customers. While not directly impacting customer base growth, nonpromotional product information facilitates the growth of the customer base by stimulating more likes. Thus, H2 is supported. The informational role of product information is beneficial not only to sales performance, but also to the growth of the customer base.

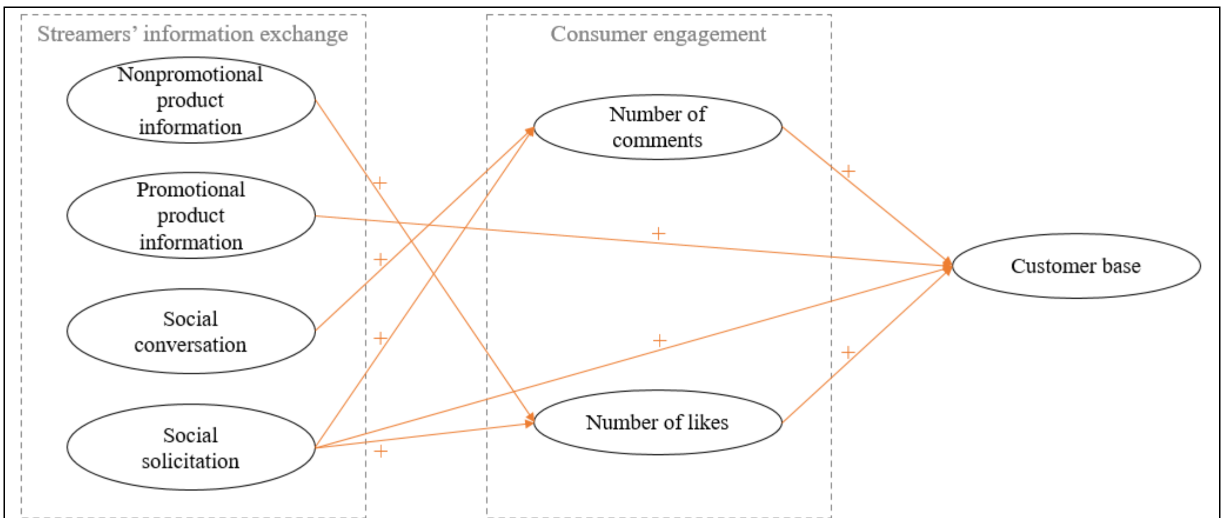

Figure 3. Main Results on Customer Base

Regarding social interactions, we find that social conversation positively affects customer base growth through higher levels of instant comments. Therefore, H4 is supported. In contrast to the direct negative effect on sales, social solicitation has a direct positive effect on the growth of the customer base. Additionally, social solicitation indirectly expands the customer base through higher consumer engagement. Hence, H6a is supported. As such, for the growth of the customer base, we find a relationship-building effect of both social conversation and social solicitation. Our results on social solicitation suggest that there is a trade-off between generating more sales in the current livestream session and growing the customer base which is beneficial to streamers in the long run.

These findings also provide evidence that consumer engagement positively impacts follower count (Bapna et al., 2019). Among the three forms of engagement, comments and likes effectively increase the customer base in the context of e-commerce livestreaming. Although we did not find a significant relationship between shares and customer base growth across all livestreams, an interesting finding is that when we remove the top 5% of livestreams in total sales, the number of shares has a significant positive effect on the number of new followers (the coefficient is 0.0164 and $p<0.05$), while our main results are robust. This suggests that for most mediocre livestreams, widespread dissemination helps them build a larger customer base, while for the top livestreams, this doesn't work probably because the streamers already have a reputation outside.

Robustness Checks

We conduct a series of robustness checks to validate and corroborate our findings. First, to ensure that our main results are not primarily driven by a few top livestreams, we exclude the top 5% of livestreams in total sales and estimate the model based on the remaining 779 livestream sessions. Second, we find that on average, purchase behavior does not occur frequently, which may cause our results to suffer from excess zeros. In our sample of 820 livestreams, the median frequency of occurrence of purchase behavior is approximately 14.6% of the periods. To address the excess-zero issue that may threaten our results, we reestimate the model on the basis of 410 livestreams where consumer purchases occur in more than 14.6% of the periods. Third, when performing unit root tests for the panel data, we follow common practice in PVAR models by stating the null hypothesis that all panels contain a unit root. This is a relatively loose criterion, as the absence of a unit root of the data for any individual livestream would allow the whole panel data to pass the test. To alleviate this concern, we unpack the panel-data unit root test by performing the test for each individual livestream. If the p-value for the unit root test is smaller than 0.1, the individual stream is deemed to not contain a unit root. The number of streams that pass unit root tests for all variables is 530 (about 65% of all 820 streams). We reestimate the model on data from only these 530 streams and all our main insights continue to hold.

In addition to the data issues pertaining to extreme observations, excess zeros in sales, and stationarity of variables, we also check the potential misspecification of the model. First, we change the dependent variable sales into the number of buyers. Second, we introduce streamer emotion as a new endogenous variable, because previous research suggests that it also evolves over time and may interact with other endogenous variables (Lin et al., 2021). We use LIWC to extract the emotion of streamers' transcribed texts. The LIWC results contain two scores representing the extent of positive and negative emotion expressed in the text. Emotion is calculated by the positive emotion score minus the negative emotion score of streamers' transcripts. Another concern is that the number of viewers may also be considered as an endogenous variable. However, the number of viewers and the number of comments are highly correlated (the correlation coefficient is 0.8462 and $p<0.01$) and thus we did not include it in the model. The results of all robustness tests are qualitatively consistent with our main analysis, which lends additional support to the key findings of this study.

Discussion and Conclusion

Theoretical Contributions

The major objective of this study is to investigate how streamers can effectively communicate with consumers in e-commerce livestreaming. Specifically, we focus on streamers' three types of information exchange (i.e., product information, social conversation, and social solicitation) and consumer engagement (i.e., comments, likes, and shares). We examine their effects on livestreaming performance in terms of both sales and customer base growth. This work contributes to the current literature on influencer marketing and livestreaming in several ways.

First, the current study contributes to the research examining the information contained in influencer-generated content. Our proposed commercial/social perspective draws on the commerciality and sociability of influencer marketing. The commercial/social perspective of information allows for a granular evaluation of influencer-generated content, especially social interactions that received less attention before but play vital roles in an interactive influencer marketing context. In addition to confirming the informational role of product information, our findings provide new insights by decomposing social interactions into social conversation and social solicitation. Our results show that social conversation has positive effects on both sales and customer base growth, while social solicitation has different effects on the dual goals, suggesting a relationship-building effect of social conversation, but both a relationship-building and a relationship-straining effect of social solicitation.

Most of previous research on influencer marketing is conducted in the context of social media rather than e-commerce. However, the insights on social media or video platforms cannot directly carry over to the e-commerce platforms. Additionally, most empirical studies on social media platforms exclusively treat consumer engagement (including comments, likes, and shares) as outcome variables, due to the constraints of collecting sales data (Mu et al., 2022). On the one hand, there is a missing link between the engagement measures and product sales on e-commerce platforms, which represent a crucial metric of e-commerce performance. On the other hand, studies on e-commerce platforms mainly focus on product sales, but little attention is paid to customer acquisition, an important long-term performance indicator for livestreaming e-commerce. We fill this research gap and empirically examine the effectiveness of influencer-generated content as well as consumer engagement on both sales and customer base growth.

Consequently, this work also contributes to the research investigating consumer engagement. While most previous research (e.g., Rishika et al., 2013) suggested a positive impact of consumer engagement on online consumption behavior. Consumers' engagement and purchase activities are integrated in the same session in the new context of e-commerce livestreaming, resulting in a higher likelihood of crowding-out effects. Our results show that the number of comments positively affects both sales and customer base growth, and the number of likes positively impacts customer base growth. However, the number of shares, a stronger signal of engagement than likes and comments (Yang et al. 2021), hurts livestreaming sales, suggesting a crowding out effect. Hence, this study echoes the call for more research on how consumer engagement affects product sales (Lee et al., 2018) by systematically examining the effects of various types of consumer engagement simultaneously in a highly integrative context of e-commerce livestreaming.

Last but not least, unlike most previous studies that focus mainly on final marketing outcomes, our research examines the dynamic process of livestreaming to capture the dynamic and interactive nature of this business context and to unravel the direct and indirect effects of streamers' information exchange. For instance, we find that streamers' social interactions with consumers stimulates more instant comments, which in turn positively impact sales and customer base growth. Therefore, this study helps to better understand the dynamics involved in e-commerce livestreaming. In addition to the direct effects of streamers' information exchange, our results provide insights into how consumers respond to streamers' information exchange, which in turn contributes to the performance of e-commerce livestreaming.

Practical Implications

This study provides important practical implications for e-commerce livestreaming platforms and streamers. Given the social nature of livestreaming, streamers should use some social conversations to build and maintain social relationships with consumers, which is important to both sales and customer base growth. Despite the significance of social conversation, product information sharing is still critical in influencing livestreaming performance. Both nonpromotional and promotional product information have direct positive effects on sales. Promotional product information is an important factor in enlarging the customer base, while nonpromotional product information also indirectly grows the customer base. However, streamers should be cautious about utilizing social solicitation and there is a trade-off between generating more current sales and expanding the customer base. If streamers place more emphasis on sales in the current session than on the growth of customer base, they would be better off avoiding the use of social solicitation, since social solicitation has a direct negative effect on sales and solicitation for shares also negatively affects sales indirectly. In contrast, if the growth of customer base is the primary goal of a livestream session, streamers can use social solicitation appropriately to directly obtain more followers and to stimulate more consumer engagement which in turn benefits customer base growth. Consumers nowadays are overwhelmed by the proliferation of livestreaming, and it seems undeniable that streamers will not succeed without engineering their livestreaming content. Findings from this study can inform content design and interaction strategies of livestreaming on e-commerce platforms.

In addition, our results provide insights for platforms to train their streamers and solve the cold-start problem in recommendation. In line with our suggestions for streamers, to foster a prosperous and sustainable business, platforms can train their streamers to exchange more product information, conduct more social conversations, and make appropriate social solicitation according to streamers' goals. Platforms also need to rationalize their recommendation decisions for a debut streamer with or without historical performance data to refer to. Based on our findings, platforms can gauge how a streamer communicates with consumers in the livestreaming to trade off sales against customer acquisition, pinpoint streamers who can achieve high performance, and further help potential rookie streamers promote the visibility of their channels.

Limitations and Future Research

Our research has several limitations. First, like many existing studies on e-commerce, our livestreaming-related dataset comes from the women's apparel category on Taobao. Although Taobao is a leading e-commerce platform and women's apparel is the largest category in livestream e-commerce, studying other platforms and categories could extend the generalizability of our findings. Second, in this study, we focus on the specific information embedded in streamers' discourse, such as social conversation and social solicitation. In addition to audio content, visual content is also an important part of livestreaming. For example, the background of studios may also influence consumers' beliefs, preferences, and behaviors. In this aspect, future research could incorporate visual content analysis into empirical models for more insights. Third, our examination of consumer behavior is at the aggregate level because of data limitations. As such, our results should be interpreted as aggregated consumer behaviors or the behavior of an average consumer in e-commerce livestreaming. Future research may collect individual consumer-level data to have a more comprehensive understanding of the heterogeneity in consumer content preference. The growth of livestream e-commerce is phenomenal. Our study helps lay a foundation for future researchers to explore in these directions in this emerging area of research.

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