Journal of Retailing and Consumer Services xxx (xxxx) 103155

Contents lists available at ScienceDirect

Journal of Retailing and Consumer Services

journal homepage: www.elsevier.com/locate/jretconser

Impact of streamers' characteristics on sales performance of search and experience products: Evidence from Douyin

Xiao Yang[a, b], Ying Liu[a, b, 1, *], Jichang Dong[a, b], Sirui Li[c, 1, *]

[a] School of Economics and Management, University of Chinese Academy of Sciences, China
[b] MOE Social Science Laboratory of Digital Economic Forecasts and Policy Simulation, University of Chinese Academy of Sciences, China
[c] ECARES, Université libre de Bruxelles, Belgium

ARTICLE INFO

Keywords:
Live streaming social commerce
Product type
Signaling theory
Gender
Assortment depth

ABSTRACT

Live streaming social commerce, a booming branch of online retailing, has enabled online retailers to interact with customers face to face, defying spatial restrictions. Recent research in live streaming social commerce has started to regard streamers' characteristics as important signals that affect customers' purchase intention. Drawing on signaling theory and the match between streamers and products, this paper aims to investigate the heterogeneous effects of streamers' objective characteristics on the sales performance of experience products and search products in the context of live streaming social commerce. Empirically, using the monthly panel data of 10,087 streamers on Douyin, this paper constructs a fixed-effect regression model to identify the effects of two streamer-centered objective signals, namely, gender and assortment depth, on streamers' sales performance. The results showed that (1) assortment depth has a positive effect on streamers' sales performance, especially when streamers have a high popularity level; (2) male streamers basically perform better in selling experience products, probably due to their high trustworthiness; and (3) female streamers perform better in selling search products, especially when the streamer has a high popularity level. These findings highlight how important it is for brands and suppliers to consider streamer-product fit when choosing suitable streamers.

1. Introduction

Live streaming social commerce is an emerging e-commerce form that adopts social media, such as live streaming and Web 2.0 technologies, in e-commerce activities (Cai et al., 2018; Guo et al., 2022). In 2020, live streaming social commerce began to rise in popularity (Ma, 2021). Douyin, which integrates e-commerce shops into its social media platform (Trendinsight, 2021a), is a representation of live streaming social commerce platforms. In August 2021, more than 30.4 billion visits were received across all streams in Douyin (Trendinsight, 2021b). Live streaming social commerce has become an important channel for online shopping and marketing.

In the research field of live streaming social commerce, a large body of literature has paid attention to how the characteristics and behaviors of streamers affect customers' purchase decisions (Guo et al., 2022; Li et al., 2021; Ma, 2021; Meng et al., 2021; Zhang et al., 2022b). However, the impact of the match between product types and streamers' characteristics in the context of live streaming social commerce has been somewhat overlooked (Yan, 2022); a few studies have noticed this issue but mainly regard product type as a direct determinant rather than a scenario that can shape the effect of streamers' characteristics on sales performance (e.g., Chen et al., 2019; Song et al., 2021).

Typically, the difference in the degree of information asymmetry between search and experience products can lead to heterogeneity in the effect of streamer-centered signals on sales (Cui et al., 2012; Ladhari et al., 2020; Park and Kim, 2018) because streamer-product fit can affect customers' purchase intention (Park and Lin, 2020). In live streaming social commerce, the gaps in search cost between the above two product types have significantly changed compared to traditional e-commerce, as the functions facilitated by live streaming technologies have lowered the difficulty of information acquisition for customers and enriched the forms of information (Lu and Chen, 2021; Sun et al., 2019; Wongkitrungrueng and Assarut, 2018). Within such a new context, there might be some changes in terms of the product-type-based

* Corresponding author. School of Economics and Management, University of Chinese Academy of Sciences, No.3, Nanyitiao, Zhongguancun, Beijing, 100190, China.
* Corresponding author.
E-mail address: liuy@ucas.ac.cn (Y. Liu).
[1] The authors contribute equally to this paper.

https://doi.org/10.1016/j.jretconser.2022.103155
Received 30 May 2022; Received in revised form 12 September 2022; Accepted 2 October 2022
0969-6989/© 20XX

effect of streamer-centered signals on sales. For example, female salespeople are usually supposed to do a better job of selling skincare and cosmetics products, a kind of experience product, in e-commerce (Beldad et al., 2016). Counterintuitively, Austin Li, a male streamer in China, has become the most favored salesperson selling skincare and cosmetics products on the live streaming e-commerce platform operated by Taobao.com; on the night of Singles' Day in 2021, 439 products were listed on his stream, nearly 300 of which were skincare and cosmetics products (Xie and Zou, 2021). Considering facts such as this, it is necessary for researchers to rethink the influence of streamer-product fit on streamers' sales performance and to help brands and suppliers select the most suitable streamers for marketing (Yan, 2022).

In practice, brands and suppliers need to evaluate many factors when choosing an appropriate streamer to fit their product. The assessment of many well-known factors—which are mostly related to customers' perception—requires brands and suppliers to carry out costly surveys on target consumers (e.g., Gao et al., 2021; Guo et al., 2022; Lee and Chen, 2021). Compared to these customer perception factors, the gender and assortment depth (i.e., the number of products within the category focused on by a streamer, Hamilton and Richards, 2009) of streamers are more intuitive and objective. Furthermore, compared to other similar streamer-focused factors, such as follower scale, selecting streamers based on the abovementioned two factors may be a more cost-effective choice for brands and suppliers because they do not need to bear additional promotion fees (e.g., premiums with respect to streamers' follower scales, Guo et al., 2022). This research aims to address the paucity of attention paid to gender and assortment depth (Chen et al., 2022; Yan, 2022) and to help brands and suppliers choose a product-fit streamer based on the two factors. Therefore, there are two research questions to be addressed: (1) How do gender and assortment depth affect streamers' sales performance? (2) Do these effects vary with product type?

Streamers, which can be regarded as influencers (Meng et al., 2021; Park and Lin, 2020), can utilize their recommendations to affect customers' purchase behavior and purchase intention (Meng et al., 2021). Gender plays an important role in the process of influencers conveying signals to viewers and is highly related to influencers' marketing effectiveness (Hudders and De Jans, 2022). At the same time, sex appeal can also affect audiences' information processing (Hou et al., 2019). For brands or suppliers, streamer gender is one of the most intuitive factors to take into consideration when choosing a suitable streamer for marketing (Hudders and De Jans, 2022). Therefore, it is worth exploring the effect of gender on streamers' sales performance in the context of live streaming social commerce.

In addition to gender, Hamilton (2009) found that assortment depth can also affect customers' choice of where to shop. With the rise of online retailing, issues relating to assortment depth have become more intricate because of consumers' implicit cognitive constraints and their desire to only process the necessary information (Sethuraman et al., 2022). Although a deeper assortment can satisfy customers' needs and provide them with abundant information to reduce choice complexity (Sethuraman et al., 2022; Vakeel et al., 2021), a few studies argue that it can also lead to a higher information cost and even information overload for customers (e.g., Sethuraman et al., 2022; Hoskins, 2020; Richards et al., 2017). In the context of live streaming social commerce, previous studies have shown some evidence about the impact of product differentiation (i.e., the number of different product categories shown in a stream) but have paid little attention to assortment depth (Chen et al., 2022; Song et al., 2021).

To address the gaps in previous literature, we draw on signaling theory to explain the effects of two streamer-centered objective signals, namely, streamer gender and assortment depth, on streamer sales performance and whether the differences between search and experience products can affect the effects. Using the monthly panel data of 10,087 streamers, we boil down our empirical questions to the evaluation of the by-product-type effect of the two signals on streamers' sales. In addition, we also examine the influence of streamers' popularity levels to reveal more details about the mechanism.

2. Theoretical background

2.1. Live streaming e-commerce

Live streaming e-commerce is a branch of social commerce with the added function of live streaming (Cai et al., 2018; Guo et al., 2022). It provides a virtual space for both sellers and customers to weaken the limitations of temporal and spatial distance (Recktenwald, 2017; Xu et al., 2020; Wongkitrungrueng and Assarut, 2018). Live streaming e-commerce can offer customers a novel experience in real-time interaction with streamers and other potential customers, streamers' real-time actions and facial expressions, and the dynamic display of products (Li et al., 2021; Lu and Chen, 2021; Wongkitrungrueng and Assarut, 2018). Based on this, studies in the literature have emerged that illustrate the characteristics of live streaming e-commerce and its influence (Hsu, 2019; Lu and Chen, 2021; Sun et al., 2019; Wongkitrungrueng and Assarut, 2018), customers' motivations for shopping on live streaming commerce platforms (Cai et al., 2018; Hou et al., 2019; Kang et al., 2021; Lee and Chen, 2021; Ma, 2021; Ming et al., 2021; Zhang et al., 2021; Zhang et al., 2022a), and the streamers and sellers' usage intentions relating to the live streaming function and their strategy for attracting customers (Guo et al., 2022; Park and Lin, 2020; Wongkitrungrueng et al., 2020; Zhao et al., 2018).

In both the fields of live streaming and retail marketing, many studies have determined that streamers/salespeople can have a huge impact on audiences/customers (Gauri et al., 2021; Hu et al., 2017; Ladhari et al., 2020; Li et al., 2021; Lin et al., 2021; Meng et al., 2021; Rapp and Beeler, 2021). In regard to live streaming e-commerce, some studies have been conducted to clarify the role of streamer characteristics in online shopping. The attractiveness, trustworthiness, and expertise of streamers are found to be positively related to customers' purchase intentions (Gao et al., 2021; Park and Lin, 2020; Xu et al., 2020). The factors that can affect customers' behavioral intentions also include the streamers' humor and sex appeal (Hou et al., 2019), their trustworthiness (Gao et al., 2021), and their social presence (Ming et al., 2021). On the basis of the literature on social judgment and interpersonal communication, Guo et al. (2022) examined the effects of streamers' characteristics from three aspects, namely, attractiveness, competence, and communication style, and then used questionnaires to determine the impact of these characteristics on customers' behavioral intentions. The authors found that beauty, expertise, humor, and passion had positive relationships with perceived hedonic value, while warmth and expertise were positively related to perceived utilitarian value. Based on these findings, this study will examine the impact of streamers' two objective characteristics, gender and assortment depth, on sales performance within the context of different product types.

2.2. Signaling theory

In consumer research, signals are informational cues that are activities or attributes of businesses in a market that convey quality information to buyers in an exchange (Cheung et al., 2014). In markets, buyers and sellers often have different amounts of information about products or services (Spence, 1973). In an environment with asymmetric information, sellers can use signals to convey unobservable information to consumers to help them assess the quality of products and services, which can reduce the perceived uncertainty and promote information exchange and trading behavior (Fan et al., 2021; Siering et al., 2018; Wells et al., 2011). The signals released by buyers include brands, warranties, and prices (Kirmani and Rao, 2000). Signaling theory can offer a framework to interpret how agents use signals to convey quality information to another party and to affect the behaviors and decisions of the signal receivers (Wells et al., 2011). Signaling theory also proposes that information asymmetry between two parties can be reduced with the help of signals (Siering et al., 2018). It has been widely applied to explain how consumers react to signals and to understand the effects of signals (Mavlanova et al., 2016).

Signaling theory has been extensively studied in management and marketing (Fan et al., 2021). In the e-commerce literature, market signals mainly include warranties, reputations, and website quality (Li et al., 2015). Live streaming social commerce can convey new kinds of signals based on streamers' identity characteristics and behavior to customers through real-time video. In addition, the degree of information asymmetry has been reduced because of the new form of product display and interaction between streamers and customers in live streaming social commerce (Lu and Chen, 2021; Sun et al., 2019; Wongkitrungrueng and Assarut, 2018). Since the signaling environment (e.g., other signals, the cost of quality information, the process of sending signals and receiving signals) can affect the effectiveness of signals (Siering et al., 2018), it might be insightful to build upon signaling theory as a theoretical lens for discussing the changes in live streaming social commerce.

Some studies in the literature have pointed out that, in e-commerce, signals can influence consumers' perceptions of product quality, risks, and trustworthiness (Fan et al., 2021; Mavlanova et al., 2016; Siering et al., 2018), thus further affecting the purchase behavior of customers (Mavlanova et al., 2016; Cheung et al., 2014). In the context of online shopping, Kozlenkova et al. (2017) found that buyers used signals generated by sellers, such as the seller's reputation and bilateral communication, to reduce the risk of online shopping. Drawing upon signaling theory, Siering et al. (2018) identified two signal types in online reviews, namely, content-related signals (the content and writing style of the review) and reviewer-related signals (reviewer professionalism and non-anonymity), and observed that both types of signals influence the helpfulness of reviews. In the context of live streaming e-commerce, Lu and Chen (2021) proposed that the physical characteristics of streamers in product trials and the value they share with viewers in real-time interaction can be regarded as two signals to benefit trust building in consumers with similar physical characteristics and values. Guided by the theoretical foundations of signaling theory, this study focused on the effect of two observable signals, the gender and assortment depth of streamers, on sales performance in live streaming scenarios.

2.3. Classification of products

Nelson's (1970) study clarified the importance of the effect of information about the quality of products on customers' behavior. According to the search cost or the accessibility of information about products or services, product type is classified into search and experience products (Nelson, 1970). In general, information is more expensive for experience products than for search products. This scheme is widely recognized by other scholars (Basu, 2018; Lu et al., 2021). Search products refer to products whose attribute information customers can easily understand before purchasing, and in which product-related information is completely symmetrical between sellers and customers (Nelson, 1970). For experience products, a trial period is needed for customers to know exactly the relevant attribute information about the products, and the search cost of relevant attribute information of experience products is higher than that of search products (Nelson, 1970).

Nelson's classification of products has been widely used in research on traditional online shopping (Lu et al., 2021). A few studies have found that the effectiveness of signals varies across different product types (e.g., Hong et al., 2017; Lu et al., 2021; Park and Kim, 2018). For example, Lu et al. (2021) found that product type significantly moderates the effect of customers' online observational learning on product sales. The times saved of the product only has a positive effect on experience products sales, not on search products sales (Lu et al., 2021). Product type can play a moderating role in the search behaviors of customers (Basu, 2018), and in the relationship between online review factors and customers' purchase behavior (Cui et al., 2012). It can also moderate the effect of information on the product description page on product sales (Lu et al., 2021), and the influence of vloggers' popularity on consumers' perception of trustworthiness and purchase intention (Hill et al., 2020).

Considering the change in the signaling environment brought by the functions facilitated by live streaming technologies in e-commerce (Lu and Chen, 2021; Wongkitrungrueng and Assarut, 2018), the differences in the signals' effectiveness between search products and experience products might also have changed. This research examines whether differences remain unchanged in the context of live streaming social commerce.

3. Research model and hypotheses

In this study, we focused on two signals generated by streamers, streamer gender and assortment depth. This study examined the effects of the two signals on streamers' sales performance and the heterogeneity of the main effects between search products and experience products. Additionally, considering the difficulty of cooperating with top streamers (Guo et al., 2022), it is necessary for brands and suppliers to choose a suitable streamer with the appropriate popularity level. Hence, this study then split the streamers into two different popularity levels in order to conduct a regression analysis on each separately to determine the effectiveness of the two signals under this condition. The research model was developed as shown in the following figure (see Fig. 1).

3.1. The main effects of streamer gender and assortment depth

3.1.1. Gender

Gender is a significant part of each salesperson's characteristics. Hudders and De Jans (2022) found that, for female customers, the

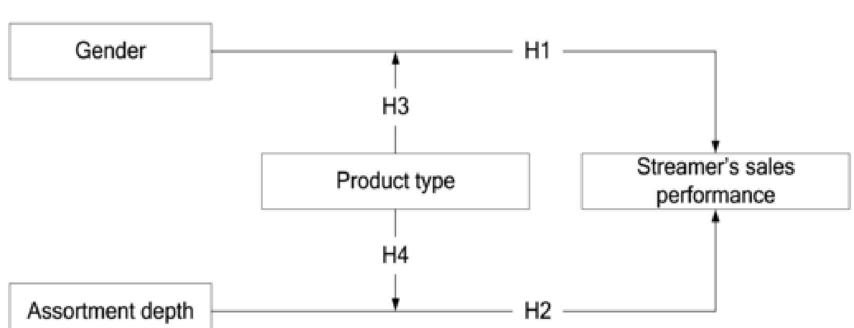

Fig. 1. The research model.

match between salespeople/influencers and customers' gender can enhance the perceived similarity of customers and strengthen the persuasive effect of salespeople/influencers on customers (Hudders and De Jans, 2022). The gender match between streamers and customers can convey the signal of the trustworthiness of streamers to customers (Hudders and De Jans, 2022), which can positively affect the customers' purchase behavior. Hence, the match effect might lead to higher sales for female salespeople. In addition, female customers experience more impulse buying (Chen et al., 2017; Lee and Chen, 2021). On Douyin, women consumed more than men from July 2020 to January 2021 (Trendinsight, 2021a). Additionally, the influencer business is mainly dominated by women in influencer marketing (Hudders and De Jans, 2022). Most of the e-commerce streamers on Douyin, which was originally a social media platform, are more like influencers. Hence, we posit the following:

H1. Female streamers have better sales performance in live streaming social commerce compared to male streamers.

3.1.2. *Assortment depth*

In this study, the assortment depth of a streamer is measured as the number of products with different website links shown in his or her streams. A common assumption in marketing is that a deeper assortment can better satisfy customer needs and thus enhance their perceived value (Sethuraman et al., 2022; Vakeel et al., 2021). A deeper assortment can convey a signal of higher service quality to customers (Ton and Raman, 2010). Additionally, in the context of live streaming, assortment depth can represent a part of network size, which is positively correlated with customers' purchase intentions (Ma, 2021). Meanwhile, some studies found that a deeper assortment might trigger the cognitive overload effect for customers and convey a signal of higher search cost to them (Hoskins, 2020; Kuksov and Villas-Boas, 2010; Sethuraman et al., 2022). In live streaming, a deeper assortment might cause customers to spend too much time watching the stream, thus reducing their satisfaction with the service. Some customers have complained that watching live streams wastes their time to some extent because they need to wait for a long time before seeing the products they want (Anonymous users, 2021). However, because of the limited time that the streamer is able to broadcast live streaming, there is also a limit to the number of products streamers can sell in one stream (Chen et al., 2022), which is similar to the shelf space in brick-and-mortar retail. Therefore, most assortments in live streaming social commerce cannot be so deep that customers incur high search costs. Thus, our second hypothesis is as follows:

H2. Assortment depth positively affects streamers' sales performance.

3.2. *The heterogeneity of the main effects by product type*

Search products, including laptops, mobile phones, and digital cameras, refer to products about which customers can obtain product information by searching (Nelson, 1970). In the case of search products, the information provided by sellers reflects objective facts. In contrast, information received by customers about experience products is subjective, which requires them to make independent judgments (Liu et al., 2016). Customers cannot comprehensively evaluate the quality until they actually experience products such as cosmetics, clothing, hotels, and books. Experience product customers rely on recommendations more than search product customers do (Basu, 2018), so the trustworthiness of streamers has a greater impact on customers' purchase decisions for experience products. Meanwhile, the signal of expertise has greater effectiveness in selling search products (Park and Kim, 2018).

Gender matching can convey the signal of the trustworthiness of streamers to customers because it can improve the persuasive effect of streamers and their perceived similarity to customers (Hudders and De Jans, 2022). For experience products, female streamers might have better sales performance in selling skincare and cosmetics products since those customers are mainly female. However, for search products, the expertise of a steamer is more important for customers when they make purchase decisions. Electronics products are mainly dominated by male salespeople (Otterbring et al., 2021), which might cause a stereotype that male salespeople are on the whole more professional in selling electronics products. At this point, the gender of male streamers could convey the signal of expertise to customers. Hence, we propose the following hypotheses:

H3a. Female streamers perform better in selling experience products than male streamers.

H3b. Male streamers perform better in selling search products than female streamers.

In terms of assortment depth, a deeper assortment can represent a higher level of service quality (Ton and Raman, 2010). Berger et al. (2007) found that perceived category expertise is positively related to assortment depth. In addition, Park and Kim (2018) found that, when considering search products, the blogger's expertise has greater effects on customers' purchase decisions. Since a deeper assortment of the streamer can signal expertise to customers, the positive effect of assortment depth might be strengthened in selling search products. Thus, we posit the following:

H4. The positive effect of assortment depth on streamers' sales performance is stronger when selling search products than when selling experience products.

4. Methodology

In this study, we chose skincare and cosmetics products to represent experience products, while 3C and home appliance products represented search products. To test the hypotheses, the data were collected from one of the most popular live streamer social commerce platforms—Douyin—which consists of 26,789 items and approximately 10,087 streamers. We employed the fixed effects model to first examine the effects of gender and assortment depth on streamers' sales performance. Then, we examined the different effectiveness of streamers' signals between search products and experience products. Moreover, we performed a median split on the streamers by the number of followers and conducted regression analysis on the two groups separately to examine whether the effectiveness of signals and the product type heterogeneity of the main effects vary by streamer's popularity level in the social media platform Douyin.

4.1. *Variable measurement*

4.1.1. *Dependent variable*

In this study, the dependent variable, namely, sales performance, is measured by the sum of the estimated sales volume of the products shown in streamer i's streams in period t ($Sales_{it}$). It represents the sales performance of a streamer. We only count the sales volume of the product that belongs to the designated category. The estimated sales volume of each product is calculated as the difference in sales volume before and after the stream.

4.1.2. *The key independent variables*

The independent variables, namely, gender and assortment depth, are measured by a dummy ($Gender_i$), designated 1 when streamer i's gender is female, and the number of products with different website links shown by streamer i in period t ($AssortDepth_{it}$), respectively. These represent the gender and assortment depth of a streamer separately. For the latter, we only take into account the number of products that belong to the designated category. Product type is measured by a dummy ($ProdType_{it}$), designated 1 when streamer i sells search products in period t and 0 when streamer i sells experience products in period t. It represents the designated type of products that the streamer sells.

4.1.3. Control variables

The control variables included the sales performance in the previous period ($Sales_{i,t-1}$), the broadcast time of the streamer, product price, and the reputation and popularity of the streamer. The broadcast time of the streamer is measured as the total duration of streamer i' streams in period t ($Tmin_{it}$). Product price is measured as the average price of products in streamer i's streams in period t ($Price_{it}$). The reputation and popularity of the streamer are measured by the two-digit decimal score given by Douyin of streamer i in period t ($Repu_{it}$) and the number of followers of streamer i in period t ($Fnum_{it}$), respectively. $Repu_{it}$ ranges from 0 to 5 (0 = "worst reputation" to 5 = "best reputation"). Some studies have indicated the positive effects of the two characteristics on streamers' sales performance (Guo et al., 2022; Ladhari et al., 2020; Wongkitrungrueng and Assarut, 2018). The description of the above-mentioned variables is shown in Table 1.

4.2. Data collection

We chose a third-party data collection tool to acquire data. This study collected details of the top 1500 streamers each month for search products and experience products from January to September 2021. The monthly sales volumes of the last few streamers in the data are sufficiently small, so the data of the top 1500 streamers would be sufficient for this study. The data include each streamer's ID, gender, and the monthly data of the streamer's reputation and number of followers, number of products shown in streams, number of stream sessions, live streaming duration, and estimated sales volume.

Table 1
The description of variables.

Variable	Description
$Sales_{it}$	The estimated sales volume of streamer i in period t.
$Gender_i$	A dummy variable. $Gender_i = 1$ if streamer i is female, otherwise, $Gender_i = 0$
$AssortDepth_{it}$	The number of the products with different website links shown by streamer i in period t divided by 100.
$ProdType_{it}$	A dummy variable. $ProdType_{it} = 1$ if streamer i sells search products in period t. $ProdType_{it} = 0$ if streamer i sells experience products in period t.
$Price_{it}$	The average price of products sold by streamer i in period t.
$Tmin_{it}$	The live streaming duration in minutes of streamer i in period t.
$Repu_{it}$	The reputation of streamer i in period t. $Repu_{it} \in [0, 5]$. 5 is the best, and 0 is the worst.
$Fnum_{it}$	The number of the fans of streamer i at 8:00 a.m. on the first day of period $t + 1$.

4.3. Basic model

We adopted a fixed-effect regression model in this study. There is an obvious Matthew effect in China's live streaming social commerce industry (Guo et al., 2022). Therefore, the extreme difference of the independent variable $Sales_{it}$ and the control variables $Price_{it}$, $Fnum_{it}$, and $Tmin_{it}$ is relatively large in this study, so the logarithm was taken to reduce the absolute value of the data, making the estimation results more stable. The basic research model used in this study is as follows. c_t in this model represents the time fixed effects, with u_i controlling the individuals' differences and random error term ε_{it}.

$$LnSales_{it} = \alpha_1 LnSales_{i,t-1} + \alpha_2 LnPrice_{it} + \alpha_3 Repu_{it} + \alpha_4 LnFnum_{it} + \alpha$$
$$c_t + u_i + \varepsilon_{it}$$

$$LnSales_{it} = \alpha_1 LnSales_{i,t-1} + \alpha_2 LnPrice_{it} + \alpha_3 Repu_{it} + \alpha_4 LnFnum_{it} + \alpha$$
$$\beta_1 Gender_i + \beta_2 AssortDepth_{it} + c_t + u_i + \varepsilon_{it}$$

$$LnSales_{it} = \alpha_1 LnSales_{i,t-1} + \alpha_2 LnPrice_{it} + \alpha_3 Repu_{it} + \alpha_4 LnFnum_{it} + \alpha$$
$$\beta_1 Gender_i + \beta_2 AssortDepth_{it} + \mu_1 ProdType_{it} \times Gender_i +$$
$$\mu_2 ProdType_{it} \times AssortDepth_{it} + c_t + u_i + \varepsilon_{it}$$

5. Empirical results

5.1. Descriptive statistical analysis

Descriptive statistical analysis of variables is presented in Panel A, Table 2. The Spearman correlation coefficient was adopted to construct the correlation analysis of variables, which is shown in Panel B. The number of observations of reputation is not equal to that of other variables. This is because Douyin requires certain data (e.g., sales records and the after-sales service records of streamers) to score streamers' rep-

Table 2
Descriptive statistical and correlation analysis of key variables.

Panel A: Descriptive statistical analysis

	Variable	Observations	Mean	S.D.	Min	Max
[1]	*Sales*	26789	15969.590	70347.230	1	4877126
[2]	*Price*	26789	544.130	1287.591	0.471	28800
[3]	*Tmin*	26789	7822.607	7175.551	0	60686.530
[4]	*Repu*	25972	4.573	0.391	3	5
[5]	*Fnum*	26789	810977.500	3053908	32	124909868
[6]	*Gender*	26789	0.794	0.405	0	1
[7]	*AssortDepth*	26789	1.017	2.876	0.010	107.240
[8]	*ProdType*	26789	0.504	0.500	0	1

Panel B: Correlation analysis

	Ln[1]	*Ln*[2]	*Ln*[3]	[4]	*Ln*[5]	[6]	[7]	[8]
Ln[1]	1							
Ln[2]	−0.601***	1						
Ln[3]	0.150***	−0.034***	1					
[4]	0.299***	−0.131***	0.077*	1				
Ln[5]	0.346***	−0.098***	−0.027***	0.257***	1			
[6]	0.175***	−0.100***	0.085***	0.091***	0.024***	1		
[7]	0.375***	−0.278***	0.028***	0.208***	0.349***	0.117***	1	
[8]	−0.696***	0.370***	−0.014**	−0.339***	−0.275***	−0.214***	−0.272***	1

Note: * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

utation. Some new streamers might not yet have reputation scores since they do not have enough transaction records.

5.2. Regression analysis

5.2.1. Regression analysis of the basic model

This section uses Stata 16.0 SE as the analysis tool. This study conducted a joint significance test of the individual effect and random effect and modified the Hausman statistics test. The results of these tests suggest the fixed effects model. The main effects estimation results of the impact of streamer characteristics on sales performance and the heterogeneity of the main effects by product type are shown in Table 3.

As shown in Model 1 of Table 3, $LnSales_{i,t-1}$, $Repu_{it}$, $Ln\ Fnum_{it}$, and $LnTmin_{it}$ have positive effects on $LnSales_{it}$ separately ($\alpha_1 = 0.106$, $p<0.01$; $\alpha_3 = 0.223$, $p<0.01$; $\alpha_4 = 1.674$, $p<0.01$; $\alpha_5 = 0.900$, $p<0.01$). $LnPrice_{it}$ is negatively correlated with $LnSales_{it}$ ($\alpha_2 = -0.711$; $p<0.01$).

As shown in Model 2, $AssortDepth_{it}$ is positively correlated with $LnSales_{it}$, while $Gender_i$ has no significant effect on $LnSales_{it}$ ($\beta_1 = -0.158$, $p>0.10$; $\beta_2 = 0.019$, $p<0.10$). These results lend credit to Hypothesis 2, while they do not support Hypothesis 1.

As shown in Model 3, only the effect of gender varies by product type. Female streamers perform better in selling search products, while male streamers perform better in selling experience products ($\beta_1 = -0.543$, $p<0.05$; $\mu_1 = 0.780$, $p<0.10$). The effect of assortment depth on sales performance exhibits no significant difference across search and experience products ($\mu_2 = -0.015$; $p>0.10$). Therefore, H3 and H4 were not supported.

5.2.2. Exploration of different popularity levels

There is a significant Matthew effect in China's live streaming commerce industry (Guo et al., 2022). As shown in the descriptive statistical analysis in Table 2, the most popular streamers have more than 120 million followers, while the minimum number of streamer fans is only 32. Correspondingly, the promotion fees charged by different streamers also vary widely. According to a report by iiMedia Research (2020), in 2020 Q1, 45.0% of Chinese e-commerce streamers had an average monthly income of less than 10000 yuan, and 23.5% of them had an average monthly income between 4500 yuan and 6000 yuan. Meanwhile, a few top streamers charge an average of 300,000–400,000 yuan to promote a product in a stream, such as Austin Li (Guo et al., 2022). Some small brands may not be able to afford the promotion fees of top streamers and need to choose some less popular streamers. In addition, the number of top streamers is limited (iiMedia Research, 2020), so some brands may need to wait for a period of time to work with the top streamers (Guo et al., 2022). These brands may also look for some less popular streamers while waiting for the top streamers. Therefore, most brands and suppliers need to work with streamers at different popularity levels and learn how to choose the most appropriate streamer in the high popularity group and the low popularity group separately.

The results in Table 3 provide some suggestions for brands and suppliers on how to select an appropriate streamer according to the gender and assortment depth of streamers under the same popularity level. However, the popularity of the streamer is also an effective signal to convey quality information to customers (Ma, 2021). Differences in popularity level might lead to a change in signaling environment, which would affect the effectiveness of other signals (Siering et al., 2018). Next, we provide some evidence that the effectiveness of streamers' signals, namely, gender and assortment depth, and the product type heterogeneity of the main effects vary by streamer's popularity level, aiming to help brands and suppliers choose the most suitable streamers for marketing when faced with streamers in the high popularity group and the low popularity group.

We first performed a median split on the streamers by the number of fans and conducted regression analysis on the two groups separately. We then tested if the coefficient difference between the groups was significant through Fisher's permutation test. The results are shown in models 1 through 3 of Table 4. The first and second columns in each model show the coefficients in the regression analysis. Column 3 of each model shows the P value of the test, with the null hypothesis being no between-group coefficient difference. A P value less than 0.1 means that the effect of the variable on sales performance between the two groups is significantly different.

The result in Model 1 of Table 4 shows that five of six control variables' coefficients have a significant between-group difference ($p<0.01$ for $LnSales_{i,t-1}$; $p<0.05$ for $LnPrice_{it}$; $p>0.10$ for $Repu_{it}$; $p<0.01$ for $LnFnum_{it}$; $p<0.01$ for $LnTmin_{it}$), except for reputation ($p>0.10$ for $Repu_{it}$).

The negative effect of product price on streamers' sales performance is stronger for streamers in the high popularity group ($\alpha_2 = -0.589$, $p<0.01$ in the low popularity group; $\alpha_2 = -0.763$, $p<0.01$ in the high popularity group). Streamers with high popularity would benefit more from an increase in scale of followers, while the broadcast time has stronger effectiveness on streamers' sales performance for less popular streamers compared to streamers with high popularity ($\alpha_4 = 1.671, p<0.01, \alpha_5 = 0.961, p<0.01$ in the low popularity group; $\alpha_4 = 2.133, p<0.01, \alpha_5 = 0.856, p<0.01$ in the high popularity group).

The result of Model 2 in Table 4 shows that the effectiveness of assortment depth varies by the popularity level of streamers ($p<0.10$ for $AssortDepth_{it}$). The positive effect of assortment depth on streamers' sales performance is only significant in the high popularity group ($\beta_2 = 0.052, p>0.10$ in the low popularity group; $\beta_2 = 0.017, p<0.10$ in the high popularity group). Although the results showed that only in the high popularity group did male streamers have better sales performance than female streamers ($\beta_1 = 0.018, p>0.10$ in the low popularity group; $\beta_2 = -0.328, p<0.05$ in the high popularity group), the result of Fisher's permutation test indicated that the effect of gender on streamers' sales performance was not significantly different between streamers in the high popularity group and those in the low popularity group ($p>0.10$ for $Gender_i$).

Table 3
Result of the basic model.

Variables	Model 1	Model 2	Model 3
$LnSales_{i,t-1}$	0.106*** (0.013)	0.106*** (0.013)	0.114*** (0.011)
$LnPrice_{it}$	−0.711*** (0.035)	−0.711*** (0.035)	−0.557*** (0.026)
$Repu_{it}$	0.223*** (0.067)	0.224*** (0.067)	0.241*** (0.064)
$LnFnum_{it}$	1.674*** (0.149)	1.674*** (0.149)	1.682*** (0.144)
$LnTmin_{it}$	0.900*** (0.025)	0.895*** (0.025)	0.892*** (0.024)
$Gender_i$		−0.158 (0.129)	−0.543** (0.259)
$AssortDepth_{it}$		0.019* (0.010)	0.027** (0.010)
$ProdType_{it}$			−3.166*** (0.41)
$ProdType_{it} \times Gender_i$			0.780* (0.399)
$ProdType_{it} \times AssortDepth_{it}$			−0.015 (0.020)
Month fixed effects	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes
Constant	−18.619*** (1.795)	−18.466*** (1.806)	−17.883*** (1.764)
R^2	0.407	0.407	0.451
Observations	5012	5012	5012

Note: To control for the potential disturbance of heterogeneity and serial correlation, clustered robust standard errors are applied to the regressions and reported in parentheses. This setting for the estimate of standard errors is also applied to all the following regressions. The number of observations is less than the total number of observations we have collected, because only some of the 1500 streamers were trackable over the months.
* $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Table 4
The result of the main effects and the heterogeneity of the main effects by product type.

Variables	Without main effect and interaction term (Model 1)			With main effect but without interaction term (Model 2)			With main effect and interaction term (Model 3)		
	Low Popularity	High Popularity	P value	Low Popularity	High Popularity	P value	Low Popularity	High Popularity	P value
$LnSales_{i,t-1}$	0.088***	0.120***	0.001	0.088***	0.120***	0.001	0.087***	0.131***	0.000
$LnPrice_{it}$	−0.589***	−0.763***	0.011	−0.588***	−0.763***	0.011	−0.589***	−0.543***	0.063
$Repu_{it}$	0.176*	0.226**	0.371	0.177*	0.227**	0.374	0.177**	0.270***	0.241
$LnFnum_{it}$	1.671***	2.133***	0.006	1.664***	2.118***	0.007	1.651***	2.075***	0.010
$LnTmin_{it}$	0.961***	0.856***	0.003	0.955***	0.850***	0.003	0.954***	0.844***	0.002
$Gender_i$				0.018	−0.328**	0.115	0.336	−0.586***	0.058
$AssortDepth_{it}$				0.052	0.017*	0.070	0.004	0.027**	0.174
$ProdType_{it}$							0.000	−3.299***	0.000
$ProdType_{it} \times Gender_i$							−0.510	0.926**	0.029
$ProdType_{it} \times AssortDepth_{it}$							0.155*	−0.021	0.005
Month fixed effects	Yes	Yes	NA	Yes	Yes	NA	Yes	Yes	NA
Individual fixed effects	Yes	Yes		Yes	Yes		Yes	Yes	
Constant	−17.23***	−25.78***		−17.16***	−25.29***		−17.04***	−24.85***	
R^2	0.412	0.410		0.413	0.411		0.414	0.474	
Observations	6290	8663		6290	8663		6290	8663	

Note: The number of observations in the high popularity group is larger than that in the low popularity group, because the streamers in the low popularity groups usually cannot stay in the top 1500.
* $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Last, the result of Model 3 in Table 4 shows that the product type heterogeneity of the main effects varies by the popularity level of streamers. The coefficients of both interaction items have significant between-group differences ($p<0.05$ for $ProdType_{it} \times Gender_i$; $p<0.01$ for $ProdType_{it} \times AssortDepth_{it}$). Only in the high popularity group do female streamers perform better in selling search products, while male streamers perform better in selling experience products ($\mu_1 = -0.510, p>0.10$ in the low popularity group; $\mu_1 = 0.926, p<0.05$ in the high popularity group). The product type heterogeneity of the effectiveness of assortment depth is only significant in the low popularity group ($\mu_2 = 0.155, p<0.10$ in the low popularity group; $\mu_2 = -0.0207, p>0.10$ in the high popularity group).

6. Discussion of the findings

This study investigates the relationship between streamers' characteristics and product sales volume and verifies the different effectiveness of signals between search products and experience products. The results support most of the hypotheses. This research has shown that (1) assortment depth is positively associated with streamers' sales performance. The gender of the streamer has no significant impact on sales volume. (2) The effect of gender on streamers' sales performance varies by product type. (3) The effectiveness of signals and the heterogeneity of the main effects by product type differ by the streamer's popularity level. The latter two findings are discussed below.

6.1. *The effects of signals and heterogeneity across search and experience products*

This study does not find gender differences in Model 2; however, as shown in Table 3, male streamers can achieve better sales performance than female streamers when selling experience products, while female streamers do better in selling search products. This finding might be because this study chose skincare and cosmetics products, whose customers are mainly female, to represent experience products. In this situation, male streamers can convey the signal of sex appeal to customers (Prendergast et al., 2014). Additionally, for experience products, it is important for customers to value the trustworthiness of the salespeople because of the lack of information before actually using these products (Cui et al., 2012; Nelson, 1970). In live streaming social commerce, when faced with experience products, customers are likely to obtain additional information provided by the streamer's real-time trials and by other viewers' reviews; therefore, they might decide to purchase products that they had not previously planned to purchase. In this situation, the credibility of this streamer is more likely decided by direct stimulation, such as their appearance. In a survey conducted in Hong Kong, male salespeople were found to be more trustworthy than were female salespeople in selling cosmetics products (Prendergast et al., 2014). Considering cultural similarities, this finding might also apply to entire Chinese markets. Therefore, the gender signal might have a different influence between the two types of products. Males can signal more trustworthiness in terms of selling experience products, thus improving sales performance.

The results show that female streamers have better performance in selling search products. Since the quality information of search products is easily accessed, male customers might watch the streams for hedonic value more than utilitarian value. The sex appeal of streamers has a positive relationship with perceived hedonic value (Guo et al., 2022). Hedonic value is positively related to watching intention and purchasing intention (Guo et al., 2022), so female streamers could attract more male viewers and male customers. However, female customers might have a higher perceived risk when purchasing online (Pascual-Miguel et al., 2015). For female customers, the gender match might convey a signal of similarity to them (Hudders and De Jans, 2022). This similarity can enhance the persuasive effect of female streamers and reduce the perceived risk of female customers (Hudders and De Jans, 2022). Female streamers might be viewed as more professional in dealing with the problems that female customers might also have, thus enhancing the purchase intentions of those female customers.

6.2. *The role of popularity level*

6.2.1. *The effects of gender and assortment depth by popularity level*

As shown in models 1 and 2 of Table 4, the effectiveness of the number of fans and broadcast time also vary by popularity level. High popularity enhances the effectiveness of the number of fans, while the broadcast time's impact becomes greater under the low popularity condition. In the high popularity situation, a live streamer might be an influencer (Chen and Lin, 2018). There is a stronger and more trust-based relationship between customers and live streamers, which can influence the customers' purchase decisions (Chen and Lin, 2018). The purchase intention of followers is emotionally influenced by streamers (Meng et al., 2021). Thus, the followers of popular streamers contribute more to the streamers' sales performance. For those less popular streamers, extending the broadcast time not only results in receiving Douyin official incentives to get publicity but also increases the likelihood that interested customers will watch the live streams. In such a case, it is easier for the less popular streamers to find some new interested customers. Last, the broadcast time also have different effectiveness on streamers' sales performance between groups.

Next, the results showed that the signal of assortment depth only works in a high popularity group. A deeper assortment can serve existing customers and attract new customers (Hamilton and Richards, 2009). In the low popularity scenario, there might be a less demand of assortment depth since the viewers is smaller and their wish list might be shorter. In addition, streamers in the low popularity group are less likely to attract new customers than streamers in the high popularity group. Therefore, a deeper assortment might be of greater benefit to streamers with high popularity. Therefore, deeper assortment leads to better performance of more popular streamers, while assortment depth has no main effects in the low popularity group.

6.2.2. The product type heterogeneity of the main effects by popularity level

From the results shown in model 3 of Table 4, the interaction term of streamer gender and product type is only significant in the high popularity group, while the interaction term of assortment depth and product type is significant in the low popularity group. The reason that the interaction term of streamer gender and product type works might be because streamers with large followings can represent high information quality (Ma, 2021). Because of the high information quality, other product-based quality signals, such as reputation, have less weight in the customers' decisions. Gender, which can provide more person-based information, would be valued more. However, the customer group and the factors to which customers attach importance vary by product type (Pascual-Miguel et al., 2015; Prendergast et al., 2014), so the gender signal also has different effects between search products and experience products. Therefore, there are differences in the sales performance of streamers of different genders between search products and experience products, which we have analyzed in Section 6.1.1, in the high popularity group.

The latter set of interaction terms shows that a deeper assortment can enhance the perceived expertise by conveying information that it is of a higher service quality (Ton and Raman, 2010), so customers can receive the expertise signal from a deeper assortment. With customers of less popular streamers relying more on other signals from the streamers to access quality information, to make up for the lower popularity of these streamers, the expertise signal conveyed by assortment depth would be enhanced in the low popularity group. For search products, the expertise of streamers is valued more by customers. Hence, in the low popularity group, the effectiveness of streamers' assortment depth is strengthened in selling search products.

7. Conclusion

7.1. Theoretical implications

This study provides useful insights into the impact of streamer characteristics in the field of live e-commerce and enriches the existing live e-commerce literature. First, we employ two new signals, streamers' gender and assortment depth, to enrich the literature on live streaming social commerce. Second, based on previous studies, we extend the current research on live streaming social commerce by using signaling theory to introduce product type as an interaction term to explore the heterogeneity of the main effects by product type. Previous studies in the field of live streaming social commerce have not clearly distinguished different types of products. Then, we find that the effectiveness of gender varies by product type. The findings provide some references for future researchers. Third, the results demonstrate that the streamers' popularity level does affect the signals' influence. Whether customers have high-quality information conveyed by high popularity affects the effectiveness of other signals on the customers. In addition, this study also contributes to the literature by presenting one of the first few studies to use panel data instead of one-period survey data.

7.2. Practical implications

The research results from this study also provide some guidance for streamers and enterprises. If suppliers or brands plan to promote their products in live streams, they should choose appropriate streamers for the type of products. When choosing streamers for experience products, priority should be given to streamers who can arouse customers' intention of impulsive consumption. In general, male streamers with high popularity are better at this. Additionally, although popular streamers have better performance, it is necessary to pay much more to hire them, and brands only have a short time to show their products in top streamers' streams. For SMEs, hiring staff to conduct live streaming promotion might be more cost-effective, especially for suppliers/brands selling search products.

7.3. Limitations and future research

In the process of performing research and writing this paper, it was found that there are still some problems that need further exploration and research. First, this study is only based on Douyin, which may lead to inadequate comprehensiveness of the study and affect its accuracy. Second, the characteristics of streamers are limited in this study. Compared with the literature, the personality of streamers is neglected in this study.

In future studies, to avoid the occurrence of the above problems and to make the samples more representative, it is necessary to further improve the collection process for the sample data, such as adding e-commerce platforms or expanding the scope of product types. In addition, for further exploration at the customer level, data can be collected on customers' personal factors and the perceived characteristics of streamers by means of questionnaire surveys or behavioral experiments. Additionally, we might focus on using fine-grained individual data of customers and streamers to further explore the problems of this study and to explore the decision-making process of customers to better understand the role of streamers in live streaming social commerce.

Funding

This work was supported by the National Natural Science Foundation of China (grant numbers 72272140, 71871210, and 71972174) and the Fundamental Research Funds for the Central Universities (grant number E1E40808).

Data availability

The authors are unable or have chosen not to specify which data has been used.

References

Anonymous users, 2021. Why do I always feel like watching live streaming in e-commerce is a waste of time? https://www.zhihu.com/question/472264297. (Accessed 11 July 2022).

Basu, S., 2018. Information search in the internet markets: experience versus search goods. Electron. Commer. Res. Appl. 30, 25–37. https://doi.org/10.1016/j.elerap.2018.05.004.

Beldad, A., Hegner, S., Hoppen, J., 2016. The effect of virtual sales agent (VSA) gender – product gender congruence on product advice credibility, trust in VSA and online vendor, and purchase intention. Comput. Hum. Behav. 60, 62–72. https://doi.org/10.1016/j.chb.2016.02.046.

Berger, J., Draganska, M., Simonson, I., 2007. The influence of product variety on brand perception and choice. Mark. Sci. 26, 460–472. https://doi.org/10.1287/

mksc.1060.0253.

Cai, J., Wohn, D.Y., Mittal, A., Sureshbabu, D., 2018. Utilitarian and hedonic motivations for live streaming shopping. In: Proceedings of the 2018 ACM International Conference on Interactive Experiences for TV and Online Video - TVX '18: ACM International Conference on Interactive Experiences for TV and Online Video. ACM, SEOUL Republic of Korea, pp. 81–88. https://doi.org/10.1145/3210825.3210837.

Chen, C.-C., Lin, Y.-C., 2018. What drives live-stream usage intention? The perspectives of flow, entertainment, social interaction, and endorsement. Telematics Inf. 35, 293–303. https://doi.org/10.1016/j.tele.2017.12.003.

Chen, T.-Y., Yeh, T.-L., Lo, W.-C., 2017. Impacts on online impulse purchase through perceived cognition. J. Int. Consum. Market. 29, 319–330. https://doi.org/10.1080/08961530.2017.1367208.

Chen, C., Hu, Y., Lu, Y., Hong, Y., 2019. Everyone can Be a star: understanding the role of live video streaming in online retail. SSRN Electron. J. 46. https://doi.org/10.2139/ssrn.3422615.

Chen, H., Dou, Y., Xiao, Y., 2022. Understanding the Role of Live Streamers in Live-Streaming E-Commerce. SSRN Electron. https://doi.org/10.2139/ssrn.4141864.

Cheung, C.M.K., Xiao, B.S., Liu, I.L.B., 2014. Do actions speak louder than voices? The signaling role of social information cues in influencing consumer purchase decisions. Decis. Support Syst. 65, 50–58. https://doi.org/10.1016/j.dss.2014.05.002.

Cui, G., Lui, H.-K., Guo, X., 2012. The effect of online consumer reviews on new product sales. Int. J. Electron. Commer. 17, 39–58. https://doi.org/10.2753/JEC1086-4415170102.

Fan, L., Zhang, X., Rai, L., 2021. When should star power and eWOM be responsible for the box office performance? - an empirical study based on signaling theory. J. Retailing Consum. Serv. 62, 102591. https://doi.org/10.1016/j.jretconser.2021.102591.

Gao, X., Xu, X.-Y., Tayyab, S.M.U., Li, Q., 2021. How the live streaming commerce viewers process the persuasive message: an ELM perspective and the moderating effect of mindfulness. Electron. Commer. Res. Appl. 49, 101087. https://doi.org/10.1016/j.elerap.2021.101087.

Gauri, D.K., Jindal, R.P., Ratchford, B., Fox, E., Bhatnagar, A., Pandey, A., Navallo, J.R., Fogarty, J., Carr, S., Howerton, E., 2021. Evolution of retail formats: past, present, and future. J. Retailing 97, 42–61. https://doi.org/10.1016/j.jretai.2020.11.002.

Guo, Y., Zhang, K., Wang, C., 2022. Way to success: understanding top streamer's popularity and influence from the perspective of source characteristics. J. Retailing Consum. Serv. 64, 102786. https://doi.org/10.1016/j.jretconser.2021.102786.

Hamilton, S.F., 2009. Excise taxes with multiproduct transactions. Am. Econ. Rev. 99, 458–471. https://doi.org/10.1257/aer.99.1.458.

Hamilton, S.F., Richards, T.J., 2009. Product differentiation, store differentiation, and assortment depth. Manag. Sci. 55, 1368–1376. https://doi.org/10.1287/mnsc.1090.1032.

Hill, S.R., Troshani, I., Chandrasekar, D., 2020. Signalling effects of vlogger popularity on online consumers. J. Comput. Inf. Syst. 60, 76–84. https://doi.org/10.1080/08874417.2017.1400929.

Hong, H., Xu, D., Wang, G.A., Fan, W., 2017. Understanding the determinants of online review helpfulness: a meta-analytic investigation. Decis. Support Syst. 102, 1–11. https://doi.org/10.1016/j.dss.2017.06.007.

Hoskins, J.D., 2020. The evolving role of hit and niche products in brick-and-mortar retail category assortment planning: a large-scale empirical investigation of U.S. consumer packaged goods. J. Retailing Consum. Serv. 57, 102234. https://doi.org/10.1016/j.jretconser.2020.102234.

Hou, F., Guan, Z., Li, B., Chong, A.Y.L., 2019. Factors influencing people's continuous watching intention and consumption intention in live streaming: evidence from China. Internet Res. 30, 141–163. https://doi.org/10.1108/INTR-04-2018-0177.

Hsu, K.K., 2019. Discussion on the live broadcast of social media and e-commerce. In: 19th International Conference on Electronic Business. Presented at the 19th International Conference on Electronic Business, Newcastle upon Tyne. U.K., pp. 178–185. Available online at: https://aisel.aisnet.org/iceb2019/10.

Hu, M., Zhang, M., Wang, Y., 2017. Why do audiences choose to keep watching on live video streaming platforms? An explanation of dual identification framework. Comput. Hum. Behav. 75, 594–606. https://doi.org/10.1016/j.chb.2017.06.006.

Hudders, L., De Jans, S., 2022. Gender effects in influencer marketing: an experimental study on the efficacy of endorsements by same- vs. other-gender social media influencers on Instagram. Int. J. Advert. 41, 128–149. https://doi.org/10.1080/02650487.2021.1997455.

iiMedia Research, 2020. 2020H1 Research Report on the status quo and trend of the career development of e-commerce streamers in China's live streaming e-commerce industry. http://mp.weixin.qq.com/s?_biz=MjM5MzUyMzE4MA==&mid=2649071281&idx=1&sn=6e68ce4e38f8046ca0155bc24b61fabf&chksm=be848a3289f303246d54d27e1b297b69ca0baa52b3e31f5675eac5d49a66e038832bca98c57b#rd. (Accessed 25 July 2022).

Kang, K., Lu, J., Guo, L., Li, W., 2021. The dynamic effect of interactivity on customer engagement behavior through tie strength: evidence from live streaming commerce platforms. Int. J. Inf. Manag. 56, 102251. https://doi.org/10.1016/j.ijinfomgt.2020.102251.

Kirmani, A., Rao, A.R., 2000. No pain, No gain: a critical review of the literature on signaling unobservable product quality. J. Mark. 64, 66–79. https://doi.org/10.1509/jmkg.64.2.66.18000.

Kozlenkova, I.V., Palmatier, R.W., Fang, E. (Er), Xiao, B., Huang, M., 2017. Online relationship formation. J. Mark. 81, 21–40. https://doi.org/10.1509/jm.15.0430.

Kuksov, D., Villas-Boas, J.M., 2010. When more alternatives lead to less choice. Mark. Sci. 29, 507–524. https://doi.org/10.1287/mksc.1090.0535.

Ladhari, R., Massa, E., Skandrani, H., 2020. YouTube vloggers' popularity and influence: the roles of homophily, emotional attachment, and expertise. J. Retailing Consum. Serv. 54, 102027. https://doi.org/10.1016/j.jretconser.2019.102027.

Lee, C.-H., Chen, C.-W., 2021. Impulse buying behaviors in live streaming commerce based on the stimulus-organism-response framework. Information 12, 241. https://doi.org/10.3390/info12060241.

Li, H., Fang, Y., Wang, Y., Lim, K.H., Liang, L., 2015. Are all signals equal? Investigating the differential effects of online signals on the sales performance of e-marketplace sellers. Inf. Technol. People 28, 699–723. https://doi.org/10.1108/ITP-11-2014-0265.

Li, Y., Li, X., Cai, J., 2021. How attachment affects user stickiness on live streaming platforms: a socio-technical approach perspective. J. Retailing Consum. Serv. 60, 102478. https://doi.org/10.1016/j.jretconser.2021.102478.

Lin, Y., Yao, D., Chen, X., 2021. Happiness begets money: emotion and engagement in live streaming. J. Mark. Res. 58, 417–438. https://doi.org/10.1177/00222437211002477.

Liu, Q., Huang, S., Zhang, L., 2016. The influence of information cascades on online purchase behaviors of search and experience products. Electron. Commer. Res. 16, 553–580. https://doi.org/10.1007/s10660-016-9220-0.

Lu, B., Chen, Z., 2021. Live streaming commerce and consumers' purchase intention: an uncertainty reduction perspective. Inf. Manag. 58, 103509. https://doi.org/10.1016/j.im.2021.103509.

Lu, J., Su, X., Diao, Y., Wang, N., Zhou, B., 2021. Does online observational learning matter? Empirical evidence from panel data. J. Retailing Consum. Serv. 60, 102480. https://doi.org/10.1016/j.jretconser.2021.102480.

Ma, Y., 2021. To shop or not: understanding Chinese consumers' live-stream shopping intentions from the perspectives of uses and gratifications, perceived network size, perceptions of digital celebrities, and shopping orientations. Telematics Inf. 59, 101562. https://doi.org/10.1016/j.tele.2021.101562.

Mavlanova, T., Benbunan-Fich, R., Lang, G., 2016. The role of external and internal signals in e-commerce. Decis. Support Syst. 87, 59–68. https://doi.org/10.1016/j.dss.2016.04.009.

Meng, L. (Monroe), Duan, S., Zhao, Y., Lü, K., Chen, S., 2021. The impact of online celebrity in livestreaming e-commerce on purchase intention from the perspective of emotional contagion. J. Retailing Consum. Serv. 63, 102733. https://doi.org/10.1016/j.jretconser.2021.102733.

Ming, J., Jianqiu, Z., Bilal, M., Akram, U., Fan, M., 2021. How social presence influences impulse buying behavior in live streaming commerce? The role of S-O-R theory. Int. J. Web Inf. Syst. 17, 300–320. https://doi.org/10.1108/IJWIS-02-2021-0012.

Nelson, P., 1970. Information and consumer behavior. J. Polit. Econ. 78, 311–329. https://doi.org/10.1086/259630.

Otterbring, T., Bhatnagar, R., Samuelsson, P., Borau, S., 2021. Positive gender congruency effects on shopper responses: field evidence from a gender egalitarian culture. J. Retailing Consum. Serv. 63, 102738. https://doi.org/10.1016/j.jretconser.2021.102738.

Park, E., Kim, B., 2018. Consumer's blog credibility and attitude toward blogger's recommended brand: the effects of perceived blogger's expertise, trustworthiness, and product type. Int. J. Pure Appl. Math. 120, 16.

Park, H.J., Lin, L.M., 2020. The effects of match-ups on the consumer attitudes toward internet celebrities and their live streaming contents in the context of product endorsement. J. Retailing Consum. Serv. 52, 101934. https://doi.org/10.1016/j.jretconser.2019.101934.

Pascual-Miguel, F.J., Agudo-Peregrina, Á.F., Chaparro-Peláez, J., 2015. Influences of gender and product type on online purchasing. J. Bus. Res. 7. https://doi.org/10.1016/j.jbusres.2015.01.050.

Prendergast, G.P., Li, S.S., Li, C., 2014. Consumer perceptions of salesperson gender and credibility: an evolutionary explanation. J. Consum. Market. 31, 200–211. https://doi.org/10.1108/JCM-09-2013-0695.

Rapp, A., Beeler, L., 2021. The state of selling & sales management research: a review and future research agenda. J. Market. Theor. Pract. 29, 37–50. https://doi.org/10.1080/10696679.2020.1860680.

Recktenwald, D., 2017. Toward a transcription and analysis of live streaming on Twitch. J. Pragmat. 115, 68–81. https://doi.org/10.1016/j.pragma.2017.01.013.

Richards, T.J., Hamilton, S.F., Yonezawa, K., 2017. Variety and the cost of search in supermarket retailing. Rev. Ind. Organ. 50, 263–285. https://doi.org/10.1007/s11151-016-9535-y.

Sethuraman, R., Gázquez-Abad, J.C., Martínez-López, F.J., 2022. The effect of retail assortment size on perceptions, choice, and sales: review and research directions. J. Retailing 98, 24–45. https://doi.org/10.1016/j.jretai.2022.01.001.

Siering, M., Muntermann, J., Rajagopalan, B., 2018. Explaining and predicting online review helpfulness: the role of content and reviewer-related signals. Decis. Support Syst. 108, 1–12. https://doi.org/10.1016/j.dss.2018.01.004.

Song, D., Chen, X., Guo, Z., Gao, X., 2021. What drives sales of e-commerce live streaming? Evidence from Taobao. In: Proceedings of the 14th China Summer Workshop on Information Management (CSWIM 2021). The 14th China Summer Workshop on Information Management (CSWIM 2021), pp. 225–231.

Spence, M., 1973. Job market signaling. Q. J. Econ. 87, 355. https://doi.org/10.2307/1882010.

Sun, Y., Shao, X., Li, X., Guo, Y., Nie, K., 2019. How live streaming influences purchase intentions in social commerce: an IT affordance perspective. Electron. Commer. Res. Appl. 37, 100886. https://doi.org/10.1016/j.elerap.2019.100886.

Ton, Z., Raman, A., 2010. The effect of product variety and inventory levels on retail store sales: a longitudinal study. Prod. Oper. Manag. 19, 546–560. https://doi.org/10.1111/j.1937-5956.2010.01120.x.

Trendinsight, 2021a. Douyin Ecological Development of E-commerce Report in 2021

[WWW Document]. URL//trendinsight.oceanengine.com/. 7.13.22.
Trendinsight, 2021b. The Insight Report of Douyin "818 Trendy Product Things Festival" in 2021. [WWW Document]. URL. https://trendinsight.oceanengine.com/arithmetic-report/detail/443. 7.13.22.
Vakeel, K.A., Fudurić, M., Malthouse, E.C., 2021. Extending variety seeking to multi-sided platforms: impact of new retailer listing. J. Retailing Consum. Serv. 59, 102382. https://doi.org/10.1016/j.jretconser.2020.102382.
Wells, J.D., Valacich, J.S., Hess, T.J., 2011. What signal are you sending? How website quality influences perceptions of product quality and purchase intentions. MIS Q. 35, 373. https://doi.org/10.2307/23044048.
Wongkitrungrueng, A., Assarut, N., 2018. The role of live streaming in building consumer trust and engagement with social commerce sellers. J. Bus. Res. 117, 543–556. https://doi.org/10.1016/j.jbusres.2018.08.032.
Wongkitrungrueng, A., Dehouche, N., Assarut, N., 2020. Live streaming commerce from the sellers' perspective: implications for online relationship marketing. J. Market. Manag. 36, 488–518. https://doi.org/10.1080/0267257X.2020.1748895.
Xie, C., Zou, Y., 2021. Austin Li sold 10.6 billion in one night, which is 10 times SKP's daily sales. We underestimated double 11 [WWW Document]. URL. https://baijiahao.baidu.com/s?id=1714469872431772531&wfr=spider&for=pc. 7.18.22.
Xu, X., Wu, J.-H., Li, Q., 2020. What drives consumer shopping behavior in live streaming commerce? J. Electron. Commer. Res. 21, 24. Available online at: http://www.jecr.org/sites/default/files/2020vol21no3_Paper4.pdf.
Yan, X., 2022. Influencing factors of consumers' purchase intention in live streaming E-commerce: a literature review. Front. Econ. Manag. 3, 8. https://doi.org/10.6981/FEM.202204_3(4).0026.
Zhang, M., Sun, L., Qin, F., Wang, G.A., 2021. E-service quality on live streaming platforms: swift guanxi perspective. J. Serv. Market. 35, 312–324. https://doi.org/10.1108/JSM-01-2020-0009.
Zhang, S., Huang, C., Li, X., Ren, A., 2022a. Characteristics and roles of streamers in e-commerce live streaming. Serv. Ind. J. 1–29. https://doi.org/10.1080/02642069.2022.2068530.
Zhang, X., Cheng, X., Huang, X., 2022b. Oh, my god, buy it!" investigating impulse buying behavior in live streaming commerce. Int. J. Hum. Comput. Interact. 1–14. https://doi.org/10.1080/10447318.2022.2076773.
Zhao, Q., Chen, C.-D., Cheng, H.-W., Wang, J.-L., 2018. Determinants of live streamers' continuance broadcasting intentions on Twitch: a self-determination theory perspective. Telematics Inf. 35, 406–420. https://doi.org/10.1016/j.tele.2017.12.018.

Xiao Yang is a Ph.D. track student at the School of Economics and Management, University of Chinese Academy of Sciences. Her research focuses on digital economy, fintech and e-commerce.

Ying Liu is an associate professor of Management Science at the School of Economics and Management, University of Chinese Academy of Sciences. His research interests include digital economics and data-driven management decision-making in E-commerce and Fintech. He has published in journals such as *Annals of Operations Research*, *R&D Management*, *Industrial Management & Data Systems*, and *Advanced Engineering Informatics*.

Jichang Dong is a Professor with the Management School, University of Chinese Academy of Sciences. His current research focuses on agent-based modeling, operations management, real estate economics and finance and e-commerce. He has published in leading journals, including *Decision Support Systems*, *European Journal of Operational Research*, and *Decision Making*.

Sirui Li is Ph.D. Candidate at ECARES, Université libre de Bruxelles. He was an affiliated research associate (master student) at the Research Center for Cyber-Economy and Knowledge Management, University of Chinese Academy of Sciences. His research interests cover the impact analysis in applied economics, development economics, and digital economy. He has published in *R&D Management*, *Electronic Commerce Research*, and *Transport Policy*.