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Growing Business in Live Commerce: A Tripartite Perspective and Product Heterogeneity

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Abstracts

Live streaming becomes an important channel helping organizations and individual sellers boost their sales. Our research takes an integrated perspective and examines the simultaneous influences of streamers-, consumers-, and products-related factors on sales volume in live commerce. We apply multiple linear regression to analyze a panel data set collected from Taobao live in Double 11, 2020, which contained 34,925 product sales records. We find that streamers' social capital, consumers' engagement, and products' live demonstration all significantly contribute to product sales volume. In addition, product heterogeneity matters in live commerce such that the effects of streamers' social capital and products' live demonstration on sales volume work only for experience products (not for search products) and for the products with less popular brands (not for the products with popular brands). Our research offers comprehensive insights for both researchers and practitioners on how to grow business in live commerce.

Keywords: live commerce, social capital, user engagement, live demonstration, sales volume, product heterogeneity

Motivation

Live commerce stands for one of the commercialization attempts in live streaming platforms (Guo et al., 2022). Live commerce allows consumers to engage in real-time virtual exploration of products and feel a sense of being in live rooms, thereby promoting product sales online (Zhang et al., 2021). Compared to the lean communication modes such as instant chat tools or recorded videos in traditional e-commerce, bullet messages and live-room responses in live commerce create a much more intimate interaction environment between sellers and buyers (Ang et al., 2018). The COVID-19 pandemic even accelerates the penetration of live commerce in the past few years (Zhang et al. 2022). During the pandemic, the proportion of consumers who purchase product via live streaming increased by 76% on average worldwide. Furthermore, Europe was the fastest growing region with 86% growth rate in live streaming shoppers. The following regions are Middle East and North America, with the growth of 76% and 68%, respectively (Chevalier, 2022). Live commerce is also popular among Chinese online shoppers. By the end of June 2022, there were about 841 million online shopping users in China, 469 million out of which were live commerce users (CNNIC, 2022).

Nevertheless, streamers as sellers still struggle with quite a few problems when growing business in live commerce. For example, the distribution of followers or potential consumers is highly skewed on live streaming platforms, and only the most popular streamers receive product or brand endorsement, making it difficult for the streamers with less followers to survive (Zhao et al., 2021). Meanwhile, streamers often find confused why product sales does not always grow along with the number of followers (Chen, Dou, and Xiao, 2022). Still other streamers devote much efforts in interacting with followers or demonstrating products through the live channel, but the sales volume during live sessions can hardly meet their expectation (Guo et al., 2022). Which factors matter when growing business in live commerce, streamers' popularity, live interaction with followers, or product demonstration? In order to resolve this puzzle, our study adopts a wholistic view and aims to explore the nuances regarding how streamers' social capital, consumers' engagement, and products' live demonstration influence sales volume in live commerce.

In the following, we first review the recent studies on live commerce and identify corresponding knowledge gaps relating to the tripartite perspective that entails streamer-, consumer-, and product-related factors. In particular, we integrate insights from traditional e-commerce literature that product-related factor is beyond live demonstration through the virtual channel, but also manifests in product type (experience vs. search products) and brand popularity (popular vs. less popular brands). Accordingly, we propose our research objectives that (1) we are to examine the impacts of streamers' social capital, consumers' engagement, and products' live demonstration on product sales in live commerce, and (2) we also investigate product heterogeneity in terms of product type and brand popularity that is embedded in the relationships between these tripartite factors and live commerce sales. We then elaborate on the panel data set, analysis procedures, and empirical findings. We discuss the implications of our study for theory and practice in the end.

Streamers, Consumers, and Products in Live Commerce

Live commerce, a new form of e-commerce mode, integrates online sales and live streaming together (Lu & Chen, 2021). On the one hand, streamers can deliver live shows relating to themselves as well as the products they sell in real time to viewers (Zhang et al., 2021), On the other hand, viewers can directly and synchronously interact with streamers through sending bullet messages, 'like's, or virtual gifts. These unique live and vivid interaction features that are not available in the traditional e-commerce settings easily arouse viewers' purchase interests and intentions (Chen, Chen, and Tian, 2022). The live commerce setting has just received researchers' attention in the past couple of years. We examine the extant literature that pertains to live commerce sales and find them converge into three streams, with each stream approaching the phenomenon of interest from either streamers', consumers', or products' viewpoint.

The first school of studies use advanced analytical tools to decode streamers' vivid expressions and emotions in live shows and examine how streamers' characteristics impact sales volume. However, results yield inconsistent evidences so far. For example, Bharadwaj et al., (2022) find that streamers emotions displayed an inverted U-shape effect on live commerce sales, whereas Lin et al. (2021) suggest that streamers' happiness effectively engages consumers and generates product sales. Luo et al. (2021) observe that streamers' different linguistic styles, appealing to personality or to logic, show controversial effects on sales volume. Languages that appealing to personality increases sales, while expressions appealing to logic decreases sales.

Another stream of studies investigates how consumers' engagement influence their purchase intentions and behaviors in live commerce. For instance, through live chat with streamers, consumers sense the product value and arouse purchase intention (Lv et al. 2018; Sun et al. 2021). Zhang et al. (2020) also suggest that consumers' real-time interactions with streamers can reduce psychological distance and perceived uncertainties, thereby promoting online purchases. Lu and Chen (2021) reveal that consumers' perceived similarity in value and physical characteristic with streamers can also reduce uncertainty perceptions and foster purchase intentions.

The third school of studies indicate that product characteristics matter in live commerce, though in a different sense from traditional e-commerce settings. Chen, Benbasat, and Cenfetelli (2017) observe the positive impact of product presentation in live sessions on consumers' purchase intentions. Still a few studies adopt a joint perspective, combining products' with streamers' characteristics together, to understand how to improve purchase intention in live commerce (Chen, Zhao, and Wang. 2022; Gao et al. 2021; Park & Lin, 2020).

In summary, the first research stream focuses on the influence of streamer-level factors on product sales, ignoring products- or consumers-related factors. The second and third research schools are mainly concerned about purchase behaviors in live commerce. Specifically, the second research school approaches live commerce purchase from the perspective of consumer perceptions, but seldom considers the effects from products' or streamers' sides; the third one debates on the influences at the product level or from both products' and streamers' sides, without considering all three aspects comprehensively. Therefore, we conclude that few studies have ever attempted to simultaneously consider streamer-, consumer-, and products-related factors to understand the sales volume live commerce.

In addition, as suggested in traditional e-commerce studies, product characteristics entail more than video demonstration. Specifically, two product characteristics have accrued much empirical evidences in the traditional e-commerce settings, but are yet to be validated in the live commerce context, namely product type and brand popularity. Products for sale online can be classified into experience or search product categories (Liu & Yu, 2022). Search products usually contain stable and measurable features, making them easier to sell than experience products in traditional e-commerce settings (Maity & Dass, 2014). Experience products appear more subjective, and their features or properties might vary from one buyer to another, giving rise to quality uncertainty and risks in online transactions (Hong & Pavlou, 2014). Traditional e-commerce settings can only provide instant chat tools or upload product demonstration videos in order to help consumers reduce information asymmetry involved in online transactions, especially for experience products. Live streaming excels beyond the lean chat tools or video records, but enables streamers to make all-round product demonstration and respond to viewers' enquiries in a synchronized manner, thereby reducing the quality uncertainty associated with experience products (Zhang et al., 2020).

Moreover, product brand conveys an important signal relating to product quality (Dean, 1999). Prior studies in traditional e-commerce settings have verified the impacts of brand characteristics on consumers' online purchases, such as brand popularity (Yao et al. 2017), brand name (Park & Lennon, 2009), brand page features (Nikbin et al., 2022), or co-branding (Yu et al., 2020). Despite the vivid and instant demonstration and interaction in live commerce, consumers still encounter the issue of information asymmetry as they did in traditional e-commerce settings (Kirmani & Rao, 2000). As such, product brand still carries a central signal of product quality or even product information (Dean, 1999). The popularity of brands help amplifies product diagnosticity and foster purchase intentions of online consumers (Liu & Yu, 2022).

Live commerce entails functionalities that allow both product information exchange and social interactions between streamers and consumers. Therefore, we follow Lu & Chen (2021) and two important routes in live commerce that distinguish from traditional e-commerce settings, namely, product route and social route, to understand consumers' purchase behaviors in this unique e-commerce context. Taking together, our study examines (1) the impacts of the three core elements in live commerce—streamers and consumers as the social route, and products as the product route—on live commerce sales, and (2) product heterogeneity in terms of product type and brand popularity as manifested in the influence strength of the three core elements on sales volume. Specifically, *social capital* refers to all the resources owned by an individual through his or her social connections (Bourdieu 1986; Coleman 1988). Putman (2000) extends the conceptualization of social capital and classifies it into two types: bridging social capital and bonding social capital. Bridging social capital consists of weak connection between people from different networks that can provide a way to acquire new information and resources, while bonding social capital are strong which usually found in dense social network of familiar individuals (e.g. close friends or family) (Hofer & Aubert 2013). With the advent of the Internet, social capital has been extended from offline into the online context of social network sites (Chen, Huang, and Davison, 2017). In live commerce context, streamers may never know any viewer, but they can get familiar through performance or interactive communication, which enables streamers to form and accumulate the weak connection with consumers. Therefore, we follow the definition of bridging social capital and define social capital as the resource of weak connection owned by streamer in live commerce. Streamers' most salient message for sales volume lies in their social capital, or their number of followers. Streamers with more followers symbolize their high level of social capital, which in turn enable them to win consumers' trust as well as purchases (Xu et al., 2022). *Consumers' engagement* in live commerce also plays a vital role in fostering online transactions, signifying the degree of interactions and connections between consumers and sellers (Hu & Chaudhry, 2020). Consumers' engagement is a critical part of relationship marketing, helping sellers better understand consumers' needs and preferences (Pansari & Kumar, 2017). Concerning product-related factors, we not only study the effects of *products' live demonstration* as the most important source of product information in live commerce on sales volume, but also take product type and brand popularity into consideration. As mentioned, product type and brand popularity are two important product characteristics that have been widely investigated in prior e-commerce studies. Given the substantial differences between traditional e-commerce and live commerce settings in seller-buyer and product-buyer interactions, we further explore the heterogeneity in this regard.

Methodology

Research samples and data collection

Our data for empirical analysis was from Taobao Live. Taobao is a popular e-commerce platform in China and has the largest live commerce traffic on its live streaming channel named Taobao Live. The monthly active users of Taobao almost reached 875 million in June 2022 (Thomala, 2022), and Taobao received more than 333 million visits per month as of July 2022 (Ma, 2022b). Started since early 2016, Taobao Live's Gross Merchandise Volume (GMV) surpassed RMB￥ 720 billion at the end of 2021, accounting for nearly 37.8 percent of the total GMV in live commerce market (Ma, 2022a). 'Double Eleven', a famous shopping festival in China, was firstly proposed by Taobao. During the pre-sale period of Double Eleven in 2022, more than 300 million consumers watched the live streaming content on Taobao Live (Alibaba, 2022). Furthermore, the number of live rooms whose transaction volume exceeded RMB￥10 million and RMB ￥ 100 million reached 632 and 62, respectively, during the Double Eleven sales period (Alibaba, 2022). Thus, Taobao Live is a representative platform for studying live commerce.

With the help of a third-party consulting firm, we obtained 48431 live sales records of 386 live shows. These live shows were all conducted by the top 500 streamers (in terms of the number of followers on Taobao) on November 11, 2020. We followed three steps for data cleansing and processing. First, we removed the sales record of the products that no longer available for sale on Taobao. Second, we took out the sales records with too long or too short live demonstration videos. Third, we also deleted the sales records of fortunate products such as coupons and links to lottery winners. We finally retained 34925 product sales records of 373 live shows to conduct next empirical analysis. We also provide a snapshot of a Taobao Live show in Figure 1, and denote the key measures in the snapshot.

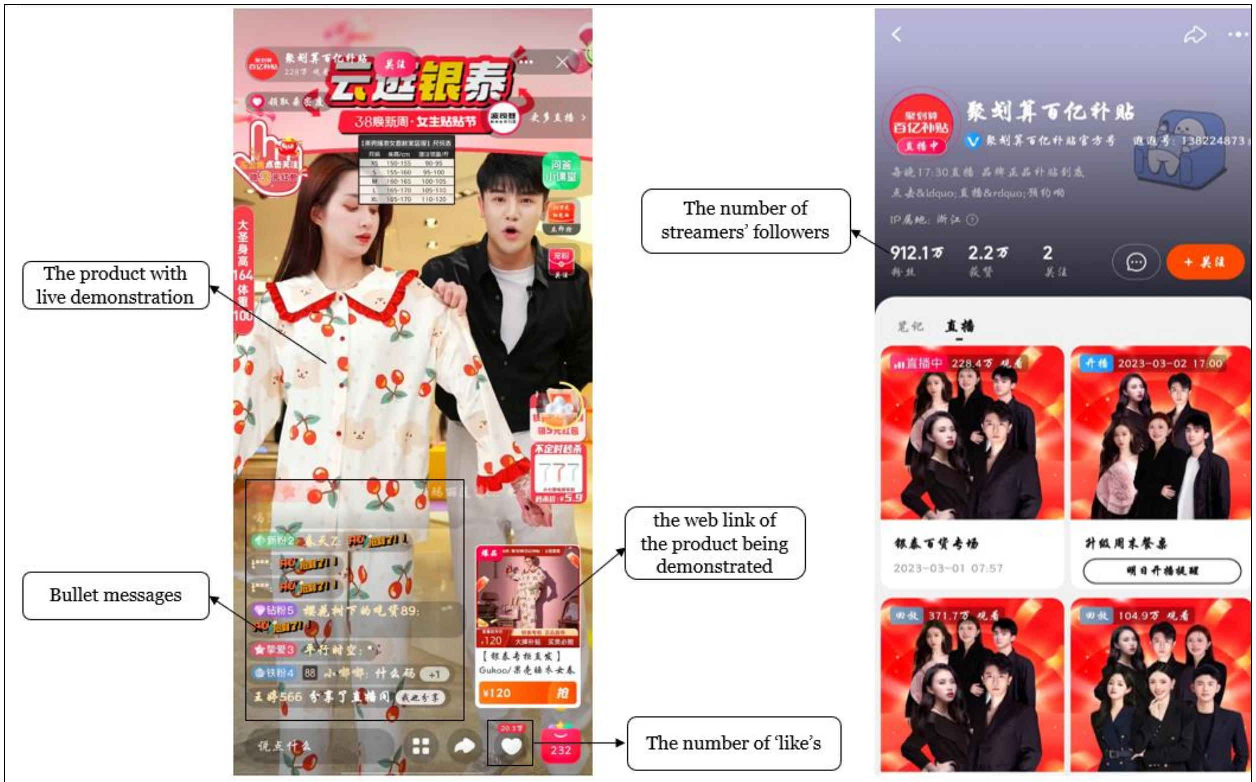

Figure 1. Snapshot of a Taobao Live Show

Measurement

Table 1 explains how we measure the dependent variable of sales volume, the three independent variables of streamers' social capital, consumers' engagement, and products' live demonstration. Specifically, the sales volume is measured by the number of products sold during the live session. Social capital has been widely considered as people's social resources from their social network (Coleman, 1988), and quantified as the number of followers in the social media context (Jin & Phua, 2014). Likewise, in live commerce, streamers contact with their followers to build their social network, so that they can use this kind of resource to improve the popularity of the live room and product sales. Therefore, the number of streamers' followers before the live session can be used to measure *streamers'* social capital. *Consumers'* engagement mainly has two types of measurement in previous literature. Some scholars used the numbers of 'like's, comments, and shares to measure it (Gruss et al., 2020), while others use consumption, contribution, and creation as measurement standard (Schivinski et al., 2016). We believe that most consumers interact with streamers through sending bullet messages and 'like's in live commerce. Therefore, *consumers'* engagement is measured by the number of bullet messages and 'like's divided by the number of products broadcasted in the live session. *Products'* live demonstration means the streamer introduces the product to consumers through live video. We calculated the demonstration video length (in minutes) of a particular product demonstrated in a live session and used it to measure *products'* live demonstration.

We also controlled for streamers' live experience, streamers' popularity, product price, product promotion, product type, product sales in the previous month, product pictures, and brand popularity to enable our results more convincing. In particular, product type and product popularity later served as the references for heterogeneity analysis.

Types	Variables	Description
Dependent variables	Sales Volume (Sales)	The number of products sold during the live session
Independent variables	*Streamers'* Social Capital (Capital)	The number of streamer's followers before the live session
	Consumers' Engagement (Engage)	The number of bullet messages and 'like's divided by the number of products broadcasted in the live session
	Products' Live Demonstration (Demo)	The video length (in minutes) of a particular product demonstrated in a live session
Control variables	Streamers' Live Experience (Exp)	The cumulative number of live sessions conducted by a streamer
	Streamers' Popularity (Pop)	Dummy variable, streamers with the top 10% number of followers as 1, others as 0
	Product Price (Price)	Product's original price
	Product Promotion (Prom)	1 subtracted by the ratio of a product's price in live session over its original price
	Product Type (Type)	Dummy variable, experience products as 1, search products as 0
	Product Sales in The Previous Month (Priorsales)	Products' sales volume in the month before the live session
	Product Pictures (Pic)	The number of pictures contained in the product link in the live session
	Brand Popularity (Brand)	Dummy variable, brands with the top 10% ranking in Baidu daily search index from May 11, 2020 to November 11, 2020 as 1, others as 0

Table 1. Key Variables

Table 2 presents the descriptive statistics for all variables. The results show that the variables are highly skewed except dummy variables and product promotion. To solve this problem, we first made a log transformation to reduce the standard value and then standardized these variables in our next regression analysis.

Variables	Mean	Std	Min	Max
Sales	547.590	4573.177	0	266400
Capital	5834451.052	7961203.582	0	42736000
Engage	1432.113	12616.512	0	325315.661
Demo	3.795	8.684	0.103	199.967
Exp	723.210	421.627	0	2484
Pop	0.130	0.332	0	1
Price	1693.408	12757.779	0.010	999999
Prom	0.382	0.267	0	0.999
Type	0.800	0.400	0	1
Priorsales	86216.624	554334.784	0	20316300
Pic	5.510	0.754	1	11
Brand	0.160	0.371	0	1

Table 2. Descriptive Statistics

Note: Sales: sales volume; Capital: *streamers'* social capital; Engage: *consumers'* engagement; Demo: *products'* live demonstration; Exp: streamers' live experience; Pop: streamers' popularity; Price: product price; Prom: product promotion; Type: product type; Priorsales: product sales in the previous month; Pic: product pictures; Brand: brand popularity.

Empirical analysis and results

Regression model

We build a multiple linear regression model to identify how these factors influence sales volume and use Stata 17.0 software to analyze our data. The model formula is described as follow:

$$\ln(Sales) = \beta_0 + \beta_1\ln(Capital) + \beta_2\ln(Engage) + \beta_3\ln(Demo) + Controls + \varepsilon$$

In this formula, β_0 is the intercept term, other β_i represents the coefficient value of variable, and ε is the error term. β_1, β_2, and β_3 are used to express the impact of *streamers'* social capital (Capital), *consumers'* engagement (Engage), and *products'* live demonstration (Demo) on sales volume (Sales). Controls is a vector of control variables, including streamers' live experience (Exp), streamers' popularity (Pop), product price (Price), product promotion (Prom), product type (Type), product sales in the previous month (Priorsales), product pictures (Pic), and brand popularity (Brand).

Main results

The results of the regression model are displayed in Table 3. Model 1 is the baseline model which is only to test the effect of control variables on sales volume. Model 2 adds the three key independent factors based on Model 1 and examines their impact on sales volume. The full sample regression results show that *streamers'* capital (β_1 = 0.055, $p<0.1$), *consumers'* engagement (β_2 = 0.170, $p<0.01$), and *products'* live demonstration (β_3 = 0.048, $p<0.01$) are all positively related to sale volume. And the effect of *consumers'* engagement is stronger than *streamers'* social capital and *products'* live demonstration. It also indicates that if the streamer has more followers, extends product demonstration length, and consumers send more bullet messages and 'like's, the product will be sold more.

Variables	Model 1	Model 2
Capital (ln)		0.055* (0.056)
Engage (ln)		0.170*** (0.000)
Demo (ln)		0.048*** (0.001)
Exp (ln)	-0.008 (0.618)	-0.013 (0.364)
Pop	0.226** (0.012)	0.005 (0.957)
Price (ln)	-0.070*** (0.000)	-0.077*** (0.000)
Prom	0.059*** (0.001)	0.054*** (0.000)
Type	0.145*** (0.001)	0.146*** (0.000)
Priorsales (ln)	0.611*** (0.000)	0.589*** (0.000)
Pic (ln)	0.014 (0.179)	0.027*** (0.004)
Brand	0.069 (0.181)	0.016 (0.675)
R^2	45.00%	48.00%

Table 3. Main Results

Note: Ln represents the logarithmic transformation of the initial variables; Sales: sales volume; Capital: *streamers'* social capital; Engage: *consumers'* engagement; Demo: *products'* live demonstration; Exp: streamers' live experience; Pop: streamers' popularity; Price: product price; Prom: product promotion; Type: product type; Priorsales: product sales in the previous month; Pic: product pictures; Brand: brand popularity. p-values in parentheses, ***p<0.01; **p<0.05; *p<0.1.

Heterogeneity analysis

We further conduct product heterogeneity analysis to investigate the differences between different product features. First, we classify products into search products and experience products based on the paradigm proposed by Nelson (Nelson, 1970, 1974). As for search products, it typically composites with many objective attributes so that consumers can find out the full information about the product and determine its quality before purchasing (Qiao et al., 2020). While for experience products, consumers can only get comprehensive quality information of the product after purchase or in the process of consumption, then they can confirm the product attributes and estimate the quality of the product (Huang et al., 2009). Therefore, consumers seldom need streamers' assistance to evaluate whether search products' function can fit their needs and make purchase decision in live commerce. However, experience products contain many subjective attributes that are hard to evaluate, leading consumers to require more information from streamers. As shown in Table 4, we find that both *streamers'* social capital and *products'* live demonstration have positive impacts on sales volume for experience products while have no influence for search products. *Consumers'* engagement can increase the sales of both experience products and search products. This result confirms the product type heterogeneity in live commerce.

Variables	Experience products		Search products	
	Model 3	Model 4	Model 5	Model 6
Capital (ln)		0.052* (0.068)		0.022 (0.279)
Engage (ln)		0.167*** (0.000)		0.145*** (0.000)
Demo (ln)		0.062*** (0.000)		-0.006 (0.778)
Exp (ln)	-0.010 (0.529)	-0.014 (0.329)	-0.055 (0.240)	-0.042 (0.300)
Pop	0.123 (0.139)	-0.052 (0.538)	0.784*** (0.000)	0.495*** (0.000)
Price (ln)	-0.050* (0.051)	-0.061*** (0.008)	-0.085*** (0.000)	-0.084*** (0.000)
Prom	0.045** (0.025)	0.045** (0.016)	0.105*** (0.000)	0.084*** (0.000)
Priorsales (ln)	0.601*** (0.000)	0.575*** (0.000)	0.659*** (0.000)	0.662*** (0.000)
Pic (ln)	0.034*** (0.002)	0.045*** (0.000)	-0.026* (0.061)	-0.019 (0.147)
Brand	0.087 (0.178)	0.024 (0.624)	0.023 (0.596)	0.033 (0.366)
R^2	42.93%	46.02%	53.26%	54.62%

Table 4. Heterogeneity Analysis Results: Experience vs. Search Products

Note: Ln represents the logarithmic transformation of the initial variables; Sales: sales volume; Capital: *streamers'* social capital; Engage: *consumers'* engagement; Demo: *products'* live demonstration; Exp: streamers' live experience; Pop: streamers' popularity; Price: product price; Prom: product promotion; Type: product type; Priorsales: product sales in the previous month; Pic: product pictures; Brand: brand popularity. p-values in parentheses, ***p<0.01; **p<0.05; *p<0.1.

Second, considering product brand is a significant signal to reflect product's quality, we also examine how product brand alters the impacts of capital, engagement, and demonstration on consumers' purchase decision and product sales (Erdem et al., 2013). In particular, we categorize product brands into popular and less popular ones using Baidu Index—a reference value reflects audience users' attention and awareness that is available on the most popular Chinese language search engine of Baidu (Huang et al., 2017; Sun et al., 2019). We used crawler to acquire each product brand's Baidu average search index during May 11, 2020 to November 11, 2020. We labeled the brands with the top 10% Baidu Index as popular brands and the rest ones as less popular brands (Wan et al. 2018). The results in Table 5 exhibit differences between popular and less popular brands. It indicates that *streamers*' social capital and *products*' live demonstration promote product sales of less popular brand products while the coefficient of these two factors are insignificant. The effect of *consumers'* engagement exists no difference.

Variables	Popular brands		Less popular brands	
	Model 7	Model 8	Model 9	Model 10
Capital (ln)		0.032 (0.121)		0.059* (0.050)
Engage (ln)		0.263*** (0.000)		0.151*** (0.000)
Demo (ln)		-0.007 (0.796)		0.056*** (0.000)
Exp (ln)	0.038 (0.482)	0.013 (0.691)	-0.010 (0.532)	-0.017 (0.254)
Pop	0.327** (0.043)	0.077 (0.501)	0.208** (0.031)	-0.003 (0.970)
Price (ln)	-0.097*** (0.006)	-0.093*** (0.006)	-0.065*** (0.002)	-0.077*** (0.000)
Prom	-0.020 (0.585)	0.010 (0.693)	0.071*** (0.000)	0.066*** (0.000)
Type	0.206** (0.028)	0.150** (0.012)	0.138** (0.001)	0.142*** (0.000)
Priorsales (ln)	0.699*** (0.000)	0.689*** (0.000)	0.595*** (0.000)	0.571*** (0.000)
Pic (ln)	-0.016 (0.408)	0.005 (0.767)	0.028** (0.011)	0.039*** (0.000)
R^2	48.37%	53.55%	44.51%	47.06%

Table 5. Heterogeneity Analysis Results: Popular vs. Less Popular Brands

Note: Ln represents the logarithmic transformation of the initial variables; Sales: sales volume; Capital: *streamers'* social capital; Engage: *consumers'* engagement; Demo: *products'* live demonstration; Exp: streamers' live experience; Pop: streamers' popularity; Price: product price; Prom: product promotion; Type: product type; Priorsales: product sales in the previous month; Pic: product pictures; Brand: brand popularity. p-values in parentheses, ***p<0.01; **p<0.05; *p<0.1.

Discussions

Our research investigates the impacts of streamers, consumers, and products on sales volume in the live commerce context. The results of empirical analysis show that *streamers'* social capital, *consumers'* engagement, and *products'* live demonstration all exhibited positive significant impacts on sales volume. The factor of consumers' engagement shows stronger predictive power than streamers' social capital and products' live demonstration do. We also explore the heterogeneity of the tripartite factors' effects in terms product type and brand popularity. We classify products into (1) experience vs. search types based on the measurability of product attributes and (2) popular vs. less popular brands according to Baidu average search index. The heterogeneity analysis results suggest that live commerce favors experience products over search products, because the sales volume of experience products was influenced by *streamers'* social capital, *consumers'* engagement, and *products'* live demonstration, but the sales volume of search products was only affected by *consumers'* engagement, which can be easily substituted by instant chat tools in alternative non-live social commerce settings. Likewise, live commerce favors the products with less popular brands, since all three factors improved the sales of less-popular-brand products, whereas only *consumers'* engagement can change the sales volume of popular-brand products.

Our research has the following theoretical contributions. First, this study proposes a comprehensive framework relating to product sales in live commerce, considering the tripartite factors of streamers, consumers, and products. Our tripartite framework extends the typology of social route and product route (Lu & Chen 2021), by further distinguishing between factors on streamers' sides vs. consumers' sides in social commerce. This framework is also in contrast with and in complementary to the prior literature that consider only one or two of the tripartite elements in live commerce settings (Bharadwaj et al. 2022; Gao et al. 2021; Yang et al. 2023). Second, we discuss the significant role of streamers' number of followers in capitalizing their livestreaming traffic into business benefits. Specifically, we proxy streamers' number of followers as their social capital and operationalize it properly in the live commerce context. Third, we examine the nuanced heterogeneity underlying in the sales of experience versus search products in live commerce. Although a number of scholars have suggested that product type matters in live commerce (Liu and Yu 2022; Zhang et al. 2020), limit empirical evidences are available regarding how experience versus search products sell differently in live commerce. Last, our analysis and findings also enrich the knowledge on the signaling effects of brand popularity in live commerce context. Still, we acknowledge a number of limitations, which help our study move toward a journal outlet. For example, in addition to product type and brand heterogeneity, we can also explore the heterogeneity behind streamer popularity. Also, beyond the linear relationships between the three important factors and sales volume, we can take into consideration of the possible non-linear effects. In doing so, our findings contribute more theoretical as well as empirical insights to the literature of e-commerce in general and live commerce in particular.

Our findings offer suggestions for streamers and platform managers to better grow business in live commerce. First, our results show that *consumers'* engagement displays the strongest impact on sales volume among the three key factors. Thus, streamers should enrich their live contents and add entertaining games or interactive shows into their live rooms, and actively respond to the enquires from consumers and inspire them to engage in live streaming sessions. Second, *streamers'* social capital and *products'* live demonstration can also positively affect sales volume. Therefore, streamers can not only improve their personalities and self-presentation style to attract more followers, but also expand products' demonstration video length to improve product sales volume. For managers, they can select streamers with more followers to boost sales volume. Third, the heterogeneity analysis results demonstrate that experience products and less-popular-brand products are more suitable for live commerce sales compared to search products and popular-brand products. In this sense, streamers may consider selling more experience products or products with less popular brands for live streaming sales in order to gain greater profits.

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