Proliferation in live streaming commerce, and key opinion leader selection

Response to reviewers

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Response to reviewers

We would like to thank the editor and the reviewers for their time to read our manuscript. Those suggestions are all valuable and helpful for revising and improving our paper. We have addressed all the concerns that reviewers raised. We listed reviewers' comments and our answers as below:
Comments from Reviewer #1:
The revised manuscript has improved a lot with due response to comments and suggestions. It is recommended to be accepted for publication.

Our answer: Thanks for your constructive suggestions that have helped improve this paper substantially. We really appreciate all your comments and suggestions.

Comments from Reviewer #2:
The current version looks much better. The authors are suggested to add a brief review of some recent analytical works in related fields to the Introduction Section. For example,

(1) Ji, X., Li, G., & Sethi, S. P. (2022). How social communications affect product line design in the platform economy. International Journal of Production Research, 60(2), 686-703.

(2) Geng, X., Guo, X., & Xiao, G. (2022). Impact of social interactions on duopoly competition with quality considerations. Management Science, 68(2), 941-959.

(3) Kuksov, D., & Liao, C. (2019). Opinion leaders and product variety. Marketing Science, 38(5), 812-834.

Our answer: Thanks for your constructive suggestions that have helped improve this paper substantially. We have revised the manuscript to review recent analytical works in related fields in the Introduction Section (Please see page 2, paragraph 2, of the revised manuscript).

Comments from Reviewer #3:
I would like to appreciate the authors revisions and responses in detail, which I think have significantly improved the early version of the manuscript. The research project have touched an emerging and very interesting business model "Live streaming commerce" and addressed the issue "how will the proliferation of live streaming commerce affect sales". Accordingly, the authors construct a two-stage moderated mediation model, and explore how the channel/stock-keeping unit proliferation affects live stream sales. The authors have well addressed the concerns suggested by the reviewers and the revised version of the manuscript well contribute the e-commerce literature. I have no further comments, and would only suggest the authors to invite

professional English editing to leverage language. Thanks again for the your well-designed work, good luck with your research!

Our answer: Thank you for your constructive suggestions that have helped improve this paper substantially. We have polished the language with the assistance of a native English speaker with a professional research background.

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Proliferation in Live Streaming Commerce, and Key Opinion Leader Selection

Abstract

Live streaming commerce is emerging as one new business model in e-commerce, with an influx of key opinion leaders (KOLs) flushing into the business as live streamers. Prior literature has noticed the improved communication channels and product differentiation of the live streaming commerce, but how will the proliferation of live streaming commerce affect sales stays under-explored. In addition, how to select the right KOL streamer is poorly understood. This study examines how the channel proliferation and stock-keeping unit proliferation affect live stream sales by increasing consumers' live streaming views converting into purchases, while the KOL's popularity, professionalism, attractiveness to female fans, and quote moderate the above mediation effect. This study contributes to the e-commerce literature by revealing the proliferation affecting sales performance mechanisms and providing practical guidance about selecting the right KOL in live streaming commerce.

Keywords: Live streaming commerce; Key Opinion Leader; SKU proliferation; channel proliferation; conversion rate

1 Introduction

As an innovative business model of e-commerce, live streaming commerce is developing rapidly and is increasingly widely adopted by both traditional e-commerce platforms and emerging platforms built by retailers [1,2,3]. Since 2016, the first year of live streaming commerce in China, the live streaming industry has developed rapidly, accelerating the integration of live streaming and e-commerce. By 2020, China's live streaming e-commerce market has exceeded 1.2 trillion RMB, with an annual growth rate of 197.0%. The number of active live streamers has also reached 1.234 million [2], with Internet celebrities, movie stars, store employees, official media, and even virtual idols flooded into the market to act as live streamers [5]. These live streamers are usually regarded as key opinion leaders (KOLs) in live streaming commerce [6].

The gradual popularization of this emerging economic model has achieved a significant breakthrough in the traditional e-commerce model. Compared with traditional e-commerce, live streaming commerce has significant advantages in better presentation channels, more interactions with customers, and an enriched shopping experience, which can stimulate consumers' willingness to buy and increase sales [7]. The two most representative features of live streaming commerce are channel proliferation and Stock-Keeping Unit (SKU) proliferation [7].

Prior literature has noticed the advantage of live streaming commerce channel proliferation compared to other business models. For instance, Sun [8] notes that traditional online channel sellers lack face-to-face, real-time customer interaction. While live streaming e-commerce has the attributes of social business and social media [9], sellers can interact with consumers in real-time through the live streaming platform, greatly reducing the perceived risk of online shopping [10-12]. Furthermore, with the development of information technology, live streaming commerce transforms the traditional presentation way with pictures/texts into videos and interactive live streams [8], which can help consumers master more detailed and comprehensive information about the product through streamers' professional descriptions and interactive Q&A [12]. Therefore, the increased channels to promote the product and interaction with consumers will largely improve consumers' trust in the product and increase their willingness to buy, which will transform into sales performance. SKU proliferation, referred to as the increase of items in each SKU in one live stream [14], is a noteworthy feature of live streaming commerce. According to prior literature, SKU proliferation could provide more options to customers, thus increasing their perceived value of the live stream [15], which will, in turn, increase consumers' purchase intentions [16-17].

Similarly, recent analytical works in related fields also suggest that the proliferation of social interactions among consumers has tremendously changed consumer behavior; therefore, firms should deeply understand their consumers' social interactions, especially when making strategic decisions [18]. Considering two major forms of social interactions, the consumer-to-consumer interactions through word-of-mouth are noteworthy. Prior literature explicitly suggests such form of social interaction as the market expansion effect and has stressed the platform's power [18]. Significantly, the market expansion can encourage the upstream firm to extend its product line while decreasing product price and quality [19]. The increase in product variety contributes to consumers' purchase decisions. However, it is dependent on opinion leaders' recommendations. In other words, considering the importance of word-of-mouth, prior analytical works examine the interplay of opinion leader recommendations and product variety in affecting consumer purchase decisions [20]. Meanwhile, it is suggested that to maximize profit, the supplier should hire a celebrity either with a large number of followers (i.e., high popularity) or with little influence but not moderate influence [21].

However, it is still unclear in the prior empirical and analytical literature how the channel/SKU proliferation affects live stream sales; in other words, the underlying mechanism of proliferation on live stream sales stays underexplored.

Moreover, prior literature has extensively examined the essential role of KOL in live streaming commerce, such as promoting consumers' purchase intention or participation [22-24], providing consumers' utilitarian or hedonic motivation [25], increasing consumers' perceived value and satisfaction [12,26] through more interactions [27-28]. Therefore, the importance of KOL in live streaming e-commerce cannot be ignored. However, although prior literature has stated that professionalism, interactivity, popularity, and commodities involvement are the essential metrics to identify a KOL [29-30], these studies have not explored the role of KOL in the live streaming commerce context. Mainly, although there is consensus that KOL could play a major role in online shopping [31-32], how to select the right KOL to present the live stream stays underexplored. Furthermore, considering the rapid development of live streaming commerce in China and the world [33], how to identify [34] and select appropriate KOL [35] in the context of live streaming proliferation emerges as an essential topic.

This paper aims to examine the following research questions: RQ1. What is the mechanism of channel/SKU proliferation affecting the sales of the live stream? RQ2. How should retailers select the right KOL in live streaming commerce to promote sales? The rest of this article is organized as follows. Section 2 reviews the literature on live streaming commerce and KOL selection and proposes our hypotheses. Section 3 introduces the research context, sample selection, and variables measurement. We then report empirical results in Section 4. Finally, section 5 summarizes theoretical implications, practical implications, and perspectives for future research.

2. Theoretical background and hypothesis development

2.1 Proliferation in Live Streaming Commerce

Live streaming commerce provides consumers instant and personalized commodities information that is highly customized to their needs [8]. The existing literature on live streaming can be divided into two research directions. The first literature stream focuses on the motivation of consumers to watch/shop through the survey data. For instance, Wongkitrungrueng and Assarut [12] investigated how consumers participate in live streaming commerce; Hou [36] found that social and structural ties directly or indirectly affect consumer participation through emotional commitment. In comparison, the second literature stream focuses on the behavior observed from actual data collected from live streaming platforms. For instance, Zhang [37] proposed a live-streaming strategy to improve customers' willingness to buy online by reducing psychological distance and perceived uncertainty. Park and Lin [38] suggested that celebrity endorsement contributes to consumers' purchase intentions. Cai [25] applied content analysis to determine the hedonic and utilitarian motivation for live shopping. Our study enriches the current literature by considering the role of channel proliferation and SKU proliferation in promoting live stream sales and the underlying mechanism. We also consider the moderating effect of KOL's features. Fig. 1 depicts the research model. We will propose the hypotheses in the following sections.

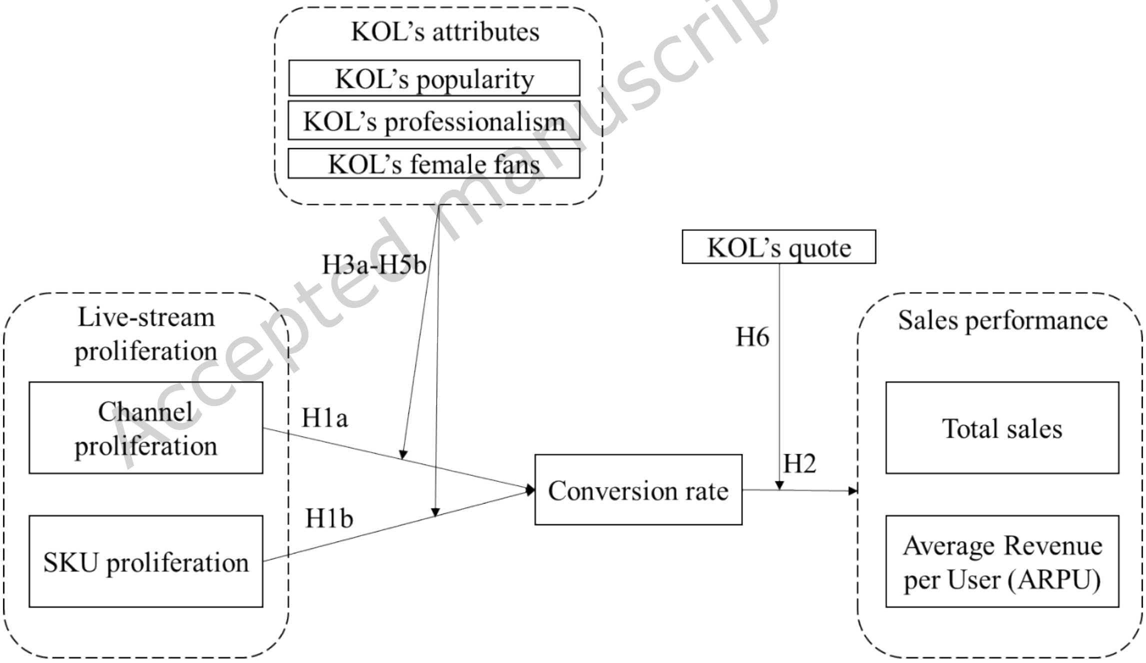

Fig. 1 Research model

2.1.1 Channel proliferation and the conversion rate of live-streaming commerce

Channel proliferation in live-streaming commerce refers to the increased interaction ways the live streamer uses to promote products to the audience [39]. Prior literature points out that the proliferation of interaction channels, especially new promotion channels with figures, texts, and videos, makes brands have more much more promotion options, enabling the combination of various communication technologies to get better access to consumers and promote brands/stores' understanding of customers [40]. The omnichannel model, proposed recently, is a result of firms seeking more channels to reach out and interact with online consumers [41].

Conversion behavior refers to converting store visits into purchases [42]. Conversion rate, defined as the percentage of virtual store visits/live streaming views that result in purchases, is an essential indicator of online shopping. Specifically, online shoppers have quite different behaviors compared to offline shopping behavior. For instance, due to meager costs (e.g., transportation costs), online shoppers are more likely to visit a virtual store without any purchase intention and delay a purchase decision until the next visit [42]. Thus, maintaining and increasing the conversion rate remains the most crucial question that e-commerce platforms need to consider [43]. We argue that channel proliferation could increase the conversion rate in live-streaming commerce.

Firstly, channel proliferation enables consumers to engage better with the live stream, which will encourage consumers to perceive the value of the live stream in a social network structure [44]. In traditional e-commerce, the interaction between brands and consumers is unilateral, while the rise of live streaming enables brands to interact with consumers in multiple ways on a real-time basis [23]. In other words, channel proliferation of live-streaming commerce provides consumers with a rich shopping experience [45], and the derived cognitive and emotional states can generate purchase intention [46].

Secondly, channel proliferation with the integration of various channels in one live stream generates a synergistic effect on consumers [47], providing more information to live stream viewers for their choice preferences, thus driving viewers to convert to purchases [48].

Taken together, we can argue that the higher the channel proliferation in the live stream, the higher the conversion rate to purchases. Accordingly, we propose the following hypothesis:

Hypothesis 1a: The channel proliferation of live streaming e-commerce is positively related to the conversion rate.

2.1.2 SKU proliferation and the conversion rate of live-streaming commerce

SKU proliferation refers to adding different forms of a similar product in the live stream. Prior literature suggests that the primary purpose of SKU proliferation is to serve different market segments to realize higher sales [14]. Although several previous studies are concerned that SKU proliferation may add to the retailer's inventory management system's complexity, cost, and extra burden, which challenges merchants' capabilities to manage the supply chain (e.g.[49]). For instance, if retailers do not effectively manage SKU proliferation, their profitability and customer satisfaction may decrease. Thus, one literature stream suggests that retailers rationalize SKUs to streamline inventory and fulfillment [49-50]. However, recent studies assert that SKU proliferation is not always harmful [14]. The reason is that with the economies of scale and scope, it is inevitable for retailers to increase their product lines to fulfill consumer demand and sustain competitive advantages [51]. We adopt this mainstream point of view and argue that SKU proliferation could contribute to increasing the conversion rate in live-streaming commerce for the following reasons:

Firstly, SKU proliferation broadens customers' perceived product availability, which makes the live stream more attractive compared to other competitors [52]. Meanwhile, SKU proliferation is more important in live streaming commerce, where most of the product categories are highly "trend-driven" [53], thus requiring retailers to respond quickly to customer needs in the marketplace by adding attractive new products [54]. Therefore, SKU proliferation provides choice flexibility, fulfilling customers' rapidly changing demands in live streaming commerce.

Secondly, consumers usually need quick decision-making in the live streaming commerce context [55], in which SKU proliferation will provide more options to consumers to increase customers' perceived value of the live stream and shopping experience [56], which will, in turn, increase consumers' conversion into purchases.

Taken together, we can argue that the higher the channel proliferation in the live stream, the higher the conversion rate to purchases. Accordingly, we propose the following hypothesis:

Hypothesis 1b: The SKU proliferation of live streaming commerce is positively related to the conversion rate.

2.2 The mediating role of conversion rate

Prior literature suggests that increased integration on an e-commerce platform positively affects consumers' conversion rate, which will, in turn, contribute to sales [57]. Specifically, according to the social learning theory, the high volume of interaction and valence on the e-commerce platform can substantially affect consumer conversion rate [57]. In other words, the channel proliferation of live streaming commerce makes information communication between sellers and online shoppers more efficient, thus making the live streaming more informing and persuading [58], which will attract more consumers to convert live streaming views into practical purchases [59]. Meanwhile, the SKU proliferation of live streaming commerce presents a high-quality cue [60]. Therefore, online shoppers will successfully receive this high-quality signal of the products promoted in the live streaming to enhance their intentions to purchase [61]. In this way, SKU proliferation in live streaming commerce, providing a wider range of consumer preferences, will give consumers more flexibility to choose, thus decreasing consumers' hesitations to purchase and increasing their conversion rate [62]. Meanwhile, a high conversion rate contributes to sales performance to a large extent [58].

Taken together, we can argue that the conversion rate mediates the relationship between proliferation and sales performance of the live stream. Accordingly, we propose the following hypothesis:

Hypothesis 2a: The channel proliferation reinforces sales performance through increased live streaming commerce conversion rate.

Hypothesis 2b: The SKU proliferation reinforces sales performance through increased live streaming commerce conversion rate.

2.3 The moderating effect of KOL in live streaming commerce

2.3.1. KOL identification

Lazarsfeld [63] first put forward the concept of "Key Opinion Leader" in the book "People's Choice" and put forward the "two-level communication" information flow model. The central role of KOL is to select/filter information and promote the formation of two-level information communication between consumers and retailers. Based on innovation diffusion theory [64], the word-of-mouth strategy suggests that KOLs are influencers, experts, and authorities [65]. In addition, KOLs usually have much more accurate product information, making them easily trusted by people.

However, not everyone can become a KOL [28]. The development of the social media era has spawned celebrities or bloggers who are not well known in mass media but have large numbers of fans. Prior literature has extensively examined how to define and systematically identify KOL in social networks. For instance, Samad [66] designed a model that estimates the main KOL's total trust value (TTV) based on the trust associations between users. In addition, many scholars have proposed new ways to identify KOL in social networks, such as through the diffusion speed and the maximum cumulative number of adopters to identify KOL [67]. The literature on identifying KOL can mainly be divided into influence-based and emotion-based. The influence-based KOL identification method mainly uses the number of fans and followers [68] to build influence indicators to identify the KOL. For instance, Google's Page Rank algorithm

[69], Cornell University's HITS algorithm [70], and corresponding variants [71-74] use social network structure in the calculation of the KOL's influence [75-76]. The emotion-based KOL identification, however, analyzes the emotional tendency of users' published text content to obtain their affective features and construct relevant classification indicators. For instance, prior literature uses emotion dictionaries or machine learning methods to identify KOL [77].

2.3.2. KOL selection in live streaming commerce

Since KOL is quite effective in live streaming commerce, how to select KOL to promote live stream sales is emerging as a hot topic [78]. Prior literature has explored several main criteria to select the appropriate KOL in live streaming commerce. For instance, Chan and Misra [79] proposed that KOL's public personality should be an essential indicator in online commerce. Flynn, Goldsmith, and Eastman [80] proposed that the KOL's influence on other consumers' purchases is the key indicator. Meng [81] summarized consumers' attention to Internet celebrities' information sources and divided them into five dimensions: credibility, professionalism, skill, interactivity, and attraction. Zhao [82], Han [83], and others have summarized the KOL characters of live streaming commerce as popularity, charm, recommendation, and presentation ways [84-85]. Previous literature has concluded that KOL is increasingly playing a significant role in live streaming commerce, where the combination between cyber-physical environment and KOL's specific features will enable the audience to obtain rich information about the product on a real-time basis. In the context of channel proliferation and SKU proliferation of live streaming commerce, we predict that KOL's popularity, professionalism, attractiveness to female fans, and quote serve as boundary conditions affecting live streaming sales.

2.3.3. KOL's popularity in living stream commerce

We now explore the moderating effect of KOL's popularity on the relationship between proliferation and the conversion rate in live streaming. The popularity of the KOL includes multiple meanings, such as his/her social status, public familiarity, and celebrity effect. The more famous the KOL, the easier for the KOL to win the trust of customers [86]. In today's digital age, the KOL-centered e-commerce business model is prevalent and is widely used as an effective marketing communication strategy [87]. Prior literature points out that streamers with a large fan base (i.e., top KOLs) can attract more live streaming resources to achieve better live stream sales [88]. However, previous research mainly focuses on the direct effect of KOL's popularity in promoting sales of live streams without examining its moderating effect in the context of live streams' proliferation. We anticipate that KOL's popularity would moderate the relationship between the proliferation and the conversion rate of the live streaming from two aspects:

On the one hand, with the rapid development of social media, popular KOLs, with higher visibility and broader influence, will generally attract more viewers to live streams [36], which makes more potential buyers realize the benefit of the SKU proliferation, thus promotes the conversion rate of live streams. On the other hand, KOL's popularity makes the viewers more willing to engage during the live stream, further strengthening viewers' interaction experience from channel proliferation [89]. The combined findings indicate that the higher the KOL's popularity, the stronger the positive effect of live streams' proliferation on conversion rate. Accordingly, we propose the following hypothesis:

Hypothesis 3a: The effect of channel proliferation on the conversion rate of the live streaming commerce is more substantial when the KOL streamer has higher popularity.

Hypothesis 3b: The effect of SKU proliferation on the conversion rate of the live streaming commerce is more substantial when the KOL streamer has higher popularity.

2.3.4. KOL's professionalism in living stream commerce

We then explore the moderating effect of KOL's professionalism on the relationship between proliferation and the conversion rate in live streaming. The professionalism of the KOL is a crucial factor in winning consumers' trust. Consumers are more willing to seek advice from professionals in shopping because professionals have rich experience, high knowledge, and skills and can easily win consumers' trust in commodities and services [90]. With the rapid development of the Internet, information generalization and information explosion are intensifying, and as a result, consumers are more eager to obtain authoritative views and professional information from professionals [30]. In live streaming e-commerce, KOL is usually expected to be specific industry professionals with a field of professional knowledge of KOL has a deeper understanding of commodities information, can release a series of professional knowledge such as commodities types, professional terms, brand, and commodities attributes, to provide users with professional opinions and enhance user' trust in the electric business platform. However, previous research mainly focuses on the direct effect of KOL's professionalism in promoting sales of live streams without examining its moderating effect in the context of live streams' proliferation. We anticipate that KOL's professionalism would moderate the relationship between the proliferation and the conversion rate of the live streaming from two aspects:

On the one hand, the KOL's professionalism makes the KOL more persuasive in promoting products. Thus, the quality of live streamed products is more trustworthy to consumers, increasing consumers' willingness to buy. Meanwhile, the more professional the KOL, the easier for viewers to percept and accept the increased benefits of KOL proliferation, further stimulating consumers' conversion into purchases. On the other hand, KOL's professionalism enables customers to be more willing to interact during the live stream [91]. Thus, the increase in interaction through channel proliferation will be more popular. The combined findings indicate that the higher the KOL's professionalism, the stronger the positive effect of live streams' proliferation on conversion rate. Accordingly, we propose the following hypothesis:

Hypothesis 4a: The effect of channel proliferation on the conversion rate of the live streaming commerce is more substantial when the KOL streamer has higher professionalism.

Hypothesis 4b: The effect of SKU proliferation on the conversion rate of the live streaming commerce is more substantial when the KOL streamer has higher professionalism.

2.3.5. KOL's attractiveness to female fans in living stream commerce

We then explore the moderating effect of KOL's attractiveness to female fans on the relationship between proliferation and the conversion rate in live streaming. As the most influential consumer group, the importance of female consumers has begun to resonate and radiate in the business field. Many well-known enterprises have adjusted their marketing strategies to target female customers [92]. Today, with the popularity of live streaming e-commerce, female consumers have gradually become an emerging economic force, attracting the attention of many market researchers. However, previous studies mainly focused on the Internet shopping behavior of female consumers, and the study of female consumption behavior in live streaming e-commerce is insufficient. Therefore, the moderating effect of the proportion of female KOL fans on live streaming sales under the background of live streaming is not investigated. We expect that the proportion of female fans of KOL will have a negative moderating effect on the relationship between live streaming proliferation and sales performance.

On the one hand, relevant studies show that emotion and cognition influence online consumers' purchase intention [93]. Compared with men, women mainly rely on the left hemisphere to process information [94] and pursue fine information processing [95]. Therefore, female consumers tend to have higher expectations for e-commerce shopping regarding emotional satisfaction. They tend to use the Internet for non-shopping purposes such as social interaction [96] and regard online shopping as a leisure activity to reduce boredom, kill time, relax and satisfy emotional needs [97-100]. At the same time, women are more likely to choose products that provide emotional value (such as clothing, cosmetics, etc.), which often take more time and energy for female consumers to select and compare. Therefore, the proliferation of live streaming will not increase female consumers' satisfaction. On the contrary, female consumers are more likely to regard multi-channels and multi-SKUs as cognitive burdens that occupy their extra time and energy.

On the other hand, trust has an important influence on purchasing decisions [101]. Previous studies have shown that female customers generally lack trust in online activities, influenced by computer anxiety [102], fear of online shopping, and fear of information privacy [103]. They exhibit lower levels of self-efficacy [104] and perceive more risks in e-commerce transactions, and this uncertainty always makes women hesitant to shop online [105]. It is not easy to make purchase decisions [106]. In addition, previous studies have pointed out that men pay more attention to the value gained from online purchases [100,107]. Therefore, the additional value provided by Channel proliferation and SKU proliferation is more likely to be perceived by males than by females.

Taken together, we suggest that although women play a decisive role in traditional shopping, the opposite is not valid in e-commerce shopping. Due to considerations of convenience, safety, and other factors [108], female consumers are usually more cautious when shopping in live streaming e-commerce, thus affecting the sales of live streaming. Specifically, male online shoppers are more likely to have goal-directed search behavior; that is, they have specific or general product purchase intention in mind when they watch live streaming and visit virtual stores, so they are less likely to exit the virtual store without a purchase [42]. On the contrary, female online shoppers are less likely to have goal-directed search behavior; thus, they are more likely to exit the virtual store without any purchases due to lacking product purchase intention.

Accordingly, we propose the following hypothesis:

Hypothesis 5a: The effect of channel proliferation on the conversion rate of the live streaming commerce is weaker when the KOL streamer has more female fans.

Hypothesis 5b: The effect of SKU proliferation on the conversion rate of the live streaming commerce is weaker when the KOL streamer has more female fans.

2.3.6. KOL's quote in living stream commerce

We then explore the moderating effect of KOL's quote on the relationship between the conversion rate and sales performance in live streaming.

Prior literature suggests that although the KOL with more substantial influence has significant commercial value in online marketing, the cost of hiring a popular KOL is not negligible. Furthermore, considering KOLs' role in live streaming commerce is becoming complex [109], recent studies are starting to be skeptical of hiring KOLs, especially considering their cost or constrained budget [110]. However, previous studies mainly focus on the interaction between KOLs/streamers and consumers, and few studies have considered the costs associated with KOLs to determine their effectiveness or flexibility [111]. Therefore, we expect that KOL's quote will negatively affect the relationship between the conversion rate and sales performance.

On the one hand, influential KOLs with a higher quote often hire teams to manage content distribution through different channels [112]. On the other hand, brands tend to hire KOLs based on their posting behavior, such as frequency, type, content, etc. However, if the KOL posts too frequently, that may distract followers' attention [113], making followers feel confused or even causing fatigue [114]. Therefore, some studies suggest that brands/retailers should select KOLs who only sustain a moderate posting activity rather than those who post too frequently, especially considering the cost of frequent postings [111].

On the other hand, prior literature also suggests that although retailers always want to hire KOL with more followers, that does not necessarily convert to higher sales performance. For one thing, the more followers, usually the higher the KOL’s quote, increasing the advertising cost. For another, prior literature points out that too many followers may even mean KOL will not pay much attention and devote lots of resources to promoting one specific product, especially when the KOL’s fans group is too large and too broad [115].

The combined findings indicate that the higher the KOL's quote, the weaker the positive effect of live streams' conversion rate on sales performance. Accordingly, we propose the following hypothesis:

Hypothesis 6: The effect of the conversion rate on the sales performance of the live streaming commerce is weaker when the KOL streamer has a higher quote.

3 Methods

3.1 Research context

To test our hypothesis, we obtained data from the global e-commerce platform Taobao Live (https://taolive.taobao.com). Taobao Live is particularly suitable for testing our hypotheses for several reasons. First, Taobao Live is the largest live streaming commerce platform with the largest KOLs group in China, which can provide us with tremendous data support. Second, Taobao Live allows each streamer to use multiple interaction ways to promote various products, which allowed us to quantify our independent variables (i.e., channel proliferation and SKU proliferation). Third, Taobao Live has an authoritative internal database: Taoshuju (https://www.taosj.com), a professional data analysis platform of Taobao Live. Taoshuju collects essential indexes such as Taobao live market flow, KOL information, store sales data, brand sales data, and hot products, which allows us to quantify various live streaming variables.

3.2 Sample and data collection

Each verified KOL can create a live ID and carry out live streams on the Taobao Live platform. For each live stream, the introduction of the KOL and the number of current viewers are displayed at the top of the page, with the product price and audience comments displayed at the bottom. In addition, the Taobao live also shows the KOL's comprehensive cability score and service score (see Fig. 2).

Fig. 2. An example of one live stream hosted by a KOL on Taobao Live

Each KOL has three ways to promote products and interact with the audience on Taobao Live. The primary presentation channel is the live stream. In addition to that, the KOL can use pre-recorded videos and text-picture descriptions to promote products better (see Fig. 2). Taobao Live will record each live stream, and critical metrics of the live stream, including duration, number of viewers, types of products, sales, number of interactions with viewers, and service ratings scored by viewers. We collected valid data from live streams from December 1st to December 31st. To ensure our samples are representative under the restrictions of crawling capacity, we excluded live streams which have not resulted in any sales. Specifically, the observation of our data sample was at the live stream-unit level.

Furthermore, we excluded live streams promoted by virtual stores/brands to ensure the sample's representativeness further. After screening, we obtained 1,519 live streams that 551 KOLs promoted. These live streams covered seven principal product categories (including beauty commodities, clothing, shoes, bags, home appliances, maternal and baby commodities, and digital products).

3.3 Variables

The independent variables are the live stream's channel and SKU proliferation. Taobao Lives provides several optional channels for streamers to interact with viewers. In addition, to live streams, each KOL can choose to use pre-recorded videos and/or text-picture descriptions to pitch to viewers. Thus, we use the number of channels the KOL uses in each live stream to interact with viewers to measure the live stream's channel proliferation (CP); where one denotes if the KOL uses live stream as the only way to interact with viewers, two denotes if the KOL uses one more other channels (no matter that is video or text/picture description, and three denotes if the KOL uses all three possible channels to interact with viewers for each live stream. SKU proliferation (SKUP) is measured by the average number of products per detailed category in a live stream [116].

The dependent variables are total sales volume and the average revenue per user of the live stream. Sales volume (SV) is measured by the number of products finally sold in the live stream [117]. The average revenue per user (ARPU) is measured by dividing the total revenue by the number of effective viewers of the live stream [118].

The mediator is the conversion rate of the live stream. The conversion rate (CR) is measured by the percentage of purchasers over the total number of live streaming viewers [62].

The first-stage moderators are the popularity, professionalism, and attractiveness of female fans of the KOL. KOL's popularity (KOLP1) is measured by the average number of viewers for all live streams hosted by the KOL in the past 30 days, adjusted by the number of the KOL's fans [119]. The KOL's average capability measures KOL's professionalism (KOLP2) in the past 30 days scored by the Taobao live [6]. KOL's female fans ratio (KOLFF) is measured by the proportion of KOL’s female fans [120]. The second-stage moderator is the KOL’s quote (KOLQ), which is measured by the average quoted price for the KOL to give a live stream [121].

The control variables for live streams include the average discount of products [1], the average response time for each interaction with viewers, and the average service score of the live stream [122]. In addition, we further control for industry and Multi-Channel-Network (MCN) to where the KOL belongs. Table 1 describes the measurement for each variable.

Table 1 Variable Descriptions.

Type	Variables	Description	References
Independent variables	Channel proliferation (CP)	Only live stream =1; live stream and one another interaction channel (e.g., pre-recorded video, text/picture combination) =2; live stream and two other interaction channels (i.e., live stream+video+text/picture) =3.	[123, 124].
	SKU proliferation (SKUP)	The average number of products per specific category in the live stream.	[125, 126].
Control variables	Discount	Average discount of products of the live stream	[127].
	Service score of the live stream (Service)	Average service rating of the live stream scored by all viewers (0-5 ratings)	[128].
	Time of response (ResponseTime)	Average response time of each interaction during the live stream (seconds, log-transformed)	[129, 130]
Mediator	Conversion rate (CR)	The percentage of purchasers over the total number of live streaming viewers	[62].
Moderators	KOL's popularity (KOLP1)	The average number of viewers for all live streams in the past 30 days, adjusted by the number of fans (log-transformed)	[131]
	KOL's professionalism (KOLP2)	Average capability rating scored by the Taobao live (log-transformed)	[132]
	KOL's quote (KOLQ)	Average quoted price for the KOL to give a live stream	[121]
	KOL's female fans ratio (KOLFF)	The proportion of the KOL's female fans	[120]
Dependent variables	Sales Volume (SV)	Number of products sold in the live stream (log-transformed)	[133]
	Average Revenue per User (ARPU)	The average revenue per each effective viewer of the live stream (log-transformed)	[134]

4. Empirical results

To ensure the consistency and validity of the model estimation, we analyzed the multicollinearity of all variables before testing hypotheses. As a result, the variance inflation factors (VIF) for all variables are smaller than 10, indicating that multicollinearity is not the study's primary concern.

4.1 Descriptive statistics

Table 2 Descriptive statistics and correlationspresents the descriptive statistics and correlations.

Table 2 Descriptive statistics and correlations (*N*=1,519)

Variables	Mean	S.D.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) SV	7.320	2.007											
(2) ARPU	0.319	0.894	0.271***										
(3) CP	1.093	0.344	0.071***	0.071***									
(4) SKUP	2.142	1.172	0.195***	0.148***	0.053***								
(5) CR	0.227	0.316	0.109***	0.057**	0.079***	0.165***							
(6) KOLP1	0.267	0.638	0.196***	0.037***	-0.069***	-0.058***	0.164***						
(7) KOLP2	6.199	0.722	0.064***	0.086***	0.081***	0.080***	-0.021*	0.275***					
(8) KOLFF	0.810	0.089	-0.044**	-0.056**	-0.103***	0.061**	0.042**	0.061**	0.153***				
(9) KOLQ	6.088	3.421	0.074**	0.011*	0.131***	-0.047**	0.067**	0.085***	0.262***	-0.158***			
(10) Discount	0.559	0.461	-0.175***	0.091***	-0.051***	0.067***	-0.080***	0.005	-0.028*	0.013*	-0.107***		
(11) Service	1.189	2.067	0.174***	0.159***	0.192***	0.044***	0.030***	0.253***	-0.123***	-0.002	0.300***	-0.029*	
(12) RT	0.434	1.036	0.114***	0.135***	0.147***	0.045***	0.022***	0.168***	0.00200	0.570***	0.156***	-0.239***	0.182***

Note. SV = Sales Volume; ARPU = Average Revenue per User; CP = Channels Proliferation; SKUP = SKU Proliferation; CR = Conversion Rate; KOLP1= KOL's Popularity; KOLP2 = KOL's Professionalism; KOLFF = KOL's Female Fans ratio; KOLQ = KOL's Quote; RT = Response Time. SV, ARPU, KOLP1, KOLP2, KOLQ, and RT are log transformed.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.2 Hypotheses testing

Table 3 shows the results for Hypothesis 1a and 1b, which predict a positive direct relationship between proliferation and conversion rate. We estimate all the models using ordinary least square (OLS) regression models. Model (1) indicates a positive and statistically significant coefficient of *Channel Proliferation (CP)* on the conversion rate (β = 0.258, S.E.= 0.089, $p < .01$). This confirms the prediction that live streams with more channel proliferation have a higher conversion rate to purchases. Models (2) and (3) indicate that these results are robust after considering the category, MCN fixed effects, and all the other control variables. Model (4) indicates a positive and statistically significant coefficient of *SKU Proliferation (SKUP)* on the conversion rate (β = 0.331, S.E.= 0.048, $p < .01$). This confirms the prediction that live streams with more SKU proliferation have a higher conversion rate to purchases. Models (5) and (6) indicate that these results are robust after considering the industry, MCN fixed effects, and all the control variables. Finally, model (7) indicates that *Channel Proliferation (CP)* and *SKU Proliferation (SKUP)* simultaneously positively affect the conversion rate of the live stream. Thus, Hypothesis 1a and 1b are supported.

4.2.1. Mediation analysis

Table 4 reports the results for Hypothesis 2a and 2b, which predict a positive indirect relationship between proliferation and sales performance mediated by the conversion rate of the live stream. The bootstrapping mediated regression analysis results show that the indirect effect of channel proliferation on sales volume is positive and statistically significant (β = 0.031, 95% Confidence Internal [0.017, 0.047]). Meanwhile, the indirect effect of channel proliferation on Average Revenue Per User is positive and statistically significant (β = 0.013, 95% Confidence Internal [0.005, 0.021]). These results are robust to two alternative widely used tests for mediation: the Sobel test and the Goodman test. Thus, hypothesis 2a receives support.

The bootstrapping mediated regression analysis results show that the indirect effect of SKU proliferation on sales volume is positive and statistically significant (β = 0.023, 95% Confidence Internal [0.009, 0.037]). Meanwhile, the indirect effect of SKU proliferation on Average Revenue Per User is positive and statistically significant (β = 0.022, 95% Confidence Internal [0.010, 0.038]). These results are robust to two alternative widely used tests for mediation: the Sobel test and the Goodman test. Thus, hypothesis 2b receives support. The results further indicate that the relationship between channel proliferation and sales volume (and Average Revenue Per User) is partially mediated by the conversion rate (i.e., there is significant direct effect of channel proliferation on sales volume (β = 0.430, S.E. = 0.099, p = .003) and Average Revenue Per User (β = 0.161, S.E. = 0.080, p = .044). Meanwhile, the relationship between SKU proliferation and sales volume (and Average Revenue Per User) is partially mediated by the conversion rate (i.e., there is significant direct effect of SKU proliferation on sales volume (β = 0.453, S.E. = 0.064, p = .000) and Average Revenue Per User (β = 0.134, S.E. = 0.046, p = .004).

Finally, the results show that the direct effect of the mediator variable (conversion rate) on sales volume is positive and statistically significant, as expected (β = 0.069, S.E. = 0.023, p = .003). meanwhlie, the direct effect of the mediator variable (conversion rate) on Average Revenue Per User is positive and statistically significant, as expected (β = 0.050, S.E. = 0.013, p = .000).

4.2.2. Moderating analysis

Table 5 reports the results for Hypothesis 3a to 5b, which predicts the relationship between proliferation and conversion rate will be moderated by KOL's popularity, professionalism, and attractiveness to female fans. Table 5 shows the ordinary least square (OLS) fixed-effects regression results using Conversion Rate (CR) as the dependent variable. All regression models control industry-fixed and MCN-fixed effects, the suppressed coefficient estimates. We mean-centered all independent variables constituting interaction terms to mitigate the potential multi-collinearity concerns [135]. To examine the moderating effects of KOLs' popularity on the relationship between channel proliferation and the conversion rate of the live stream, we included the interaction terms between the *KOL's popularity (KOLP1)* and *Channel Proliferation (CP)* in Model (1) in Table 5. If the interaction term coefficient is significant, the moderating effect should be identified. For instance, model (1) shows that the coefficient of interest is 0.24, which is significant at the 5% level. This result suggests that the KOL's popularity strengthens the positive relationship between channel proliferation and the conversion rate of the live stream. Therefore, Hypothesis 3a is further supported. To examine the moderating effects of KOLs' popularity on the relationship between SKU proliferation and the conversion rate of the live stream, we included the interaction terms between the *KOL's popularity (KOLP1)* and *SKU Proliferation (SKUP)* in Model (4) in Table 5. If the interaction term coefficient is significant, the moderating effect should be identified. Model (4) shows that the coefficient of interest is 0.488, which is significant at the 1% level. This result suggests that the KOL's popularity strengthens the positive relationship between SKU proliferation and the conversion rate of the live stream. Therefore, Hypothesis 3b is supported.

Similarly, to examine the moderating effects of KOLs' professionalism on the relationship between channel proliferation and the conversion rate of the live stream, we included the interaction terms between the *KOL's professionalism (KOLP2)* and *Channel Proliferation (CP)* in Model (2) in Table 5. Model (2) shows that the coefficient of interest is 0.116, which is significant at the 10% level. This result suggests that the KOL's professionalism strengthens the positive relationship between channel proliferation and the conversion rate of the live stream. Therefore, Hypothesis 4a is supported. Finally, to examine the moderating effects of KOLs' professionalism on the relationship between SKU proliferation and the conversion rate of the live stream, we included the interaction terms between the *KOL's professionalism (KOLP2)* and *SKU Proliferation (SKUP)* in Model (5) in Table 5. If the interaction term coefficient is significant, the moderating effect should be identified. For example, model (5) shows that the coefficient of interest is 0.163, which is significant at the 1% level. This result suggests that the KOL's professionalism strengthens the positive relationship between SKU proliferation and the conversion rate of the live stream. Therefore, Hypothesis 4b is supported.

Finally, to examine the moderating effects of KOLs' attractiveness to female fans on the relationship between channel proliferation and the conversion rate of the live stream, we included the interaction terms between the *KOL's female fans ratio(KOLFF)* and *Channel Proliferation (CP)* into Model (3) in Table 5. Model (2) shows that the coefficient of interest is -0.024, which is significant at the 10% level. This result suggests that the KOL's attractiveness to female fans weakens the positive relationship between channel proliferation and the conversion rate of the live stream. Therefore, Hypothesis 5a is supported. To examine the moderating effects of KOLs' attractiveness to female fans on the relationship between SKU proliferation and the conversion rate of the live stream, we included the interaction terms between the *KOL's female fans ratio (KOLFF)* and *SKU Proliferation (SKUP)* in Model (6) in Table 5. If the interaction term coefficient is significant, the moderating effect should be identified. Model (6) shows that the coefficient of interest is -0.054, which is significant at the 10% level. This result suggests that the KOL's attractiveness to female fans weakens the positive relationship between SKU proliferation and the conversion rate of the live stream. Therefore, Hypothesis 5b is supported.

Table 3 Regression results: The effect of Channel/SKU proliferation on the Conversion rate. OLS regressions.

Variables	(1) CR	(2) CR	(3) CR	(4) CR	(5) CR	(6) CR	(7) CR
CP	0.258***	0.240***	0.220**				0.250***
	(0.089)	(0.089)	(0.090)				(0.090)
SKUP				0.331***	0.299***	0.299***	0.308***
				(0.048)	(0.053)	(0.053)	(0.053)
Discount			0.074			0.107*	0.097
			(0.064)			(0.064)	(0.064)
Service			0.014			0.015	0.023
			(0.024)			(0.024)	(0.024)
RT			-0.179***			-0.180***	-0.163**
			(0.069)			(0.068)	(0.068)
Category FE	No	Yes	Yes	No	Yes	Yes	Yes
MCN FE	No	Yes	Yes	No	Yes	Yes	Yes
_cons	0.982***	0.837***	1.291***	-0.614***	-0.650***	-0.159	0.019
	(0.110)	(0.168)	(0.253)	(0.194)	(0.251)	(0.328)	(0.333)
N	1519	1519	1519	1519	1519	1519	1519
R^2	0.005	0.022	0.026	0.030	0.037	0.043	0.048

Note. CR = Conversion Rate; CP = Channels Proliferation; SKUP = SKU Proliferation; RT = Response Time; MCN = Multi-Channel Network.

Note. Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4 Results of bootstrapping mediation regression analysis

	Dependent variable: Sales Volume						Dependent variable: Average Revenue Per User					
Independent variables	***β***	***SE***	***p***	**95% CI**	**Sobel**	**Goodman**	***β***	***SE***	***p***	**95% CI**	**Sobel**	**Goodman**
Indirect effects mediated by conversion rate												
Channel proliferation	0.031	NA	NA	0.017, 0.047	YES	YES	0.013	NA	NA	0.005, 0.021	YES	YES
SKU proliferation	0.023	NA	NA	0.009, 0.037	YES	YES	0.022	NA	NA	0.010, 0.038	YES	YES
Direct effects												
Channel proliferation	0.403	0.099	0.000	0.193, 0.589	-	-	0.161	0.080	0.044	0.019, 0.349	-	-
SKU proliferation	0.453	0.064	0.000	0.328, 0.578			0.134	0.046	0.004	0.045, 0.221		
Total effects												
Channel proliferation	0.433	0.098	0.000	0.221, 0.622	-	-	0.174	0.080	0.030	0.030, 0.363	-	-
SKU proliferation	0.476	0.064	0.000	0.353, 0.597			0.156	0.045	0.013	0.043, 0.218		
Conversion rate	0.069	0.023	0.003	0.028, 0.123	-	-	0.050	0.013	0.000	0.021, 0.074	-	-

Note: Generalized structural equation modeling fits a single model and estimates both indirect and direct effects (Hayes & Preacher, 2013), in contrast to traditional mediation analysis that involves a series of linear regression models (Baron & Kenny, 1986). A vital advantage of this approach is that it allows the residuals to vary. We employed bootstrapping with 5000 replications to test the significance of the indirect paths from the independent variables (Channel proliferation and SKU proliferation) to the dependent variable (Sales Volume and Average Revenue Per User) through the mediator (Conversion rate). Bootstrapping is a nonparametric approach that imposes no assumptions about the distributions of the variables or the sampling distribution of the statistic. We reported Bias-Corrected and accelerated (BCa) confidence intervals for each parameter estimated in the mediation model.

Table 5 Moderating effects of KOL's features on the relationship between Channel/SKU proliferation and the Conversion rate

Variables	(1) CR	(2) CR	(3) CR	(4) CR	(5) CR	(6) CR
CP	0.047 (0.033)	0.101** (0.042)	0.084** (0.038)			
SKUP				0.148*** (0.045)	0.259*** (0.048)	0.282*** (0.052)
KOLP1	1.093*** (0.058)			0.931*** (0.058)		
KOLP2		0.069 (0.048)			-0.059 (0.055)	
KOLFF			0.166*** (0.042)			0.167*** (0.041)
CP×KOLP1	0.240** (0.099)					
CP×KOLP2		0.116* (0.053)				
CP×KOLAF			-0.024* (0.013)			
SKUP×KOLP1				0.488*** (0.063)		
SKUP×KOLP2					0.163*** (0.061)	
SKUP×KOLFF						-0.054* (0.030)
Discount	0.021 (0.056)	0.043 (0.058)	0.080 (0.064)	0.052 (0.056)	0.063 (0.058)	0.110* (0.063)
Service	-0.011 (0.021)	0.056** (0.024)	0.019 (0.024)	0.009 (0.021)	0.055** (0.024)	0.021 (0.024)
RT	-0.011 (0.061)	-0.166** (0.066)	-0.192*** (0.069)	0.005 (0.059)	-0.168*** (0.064)	-0.192*** (0.068)
Category FE	Yes	Yes	Yes	Yes	Yes	Yes
MCN FE	Yes	Yes	Yes	Yes	Yes	Yes
_cons	0.440** (0.214)	0.781*** (0.230)	1.065*** (0.242)	0.339 (0.209)	0.845*** (0.227)	1.110*** (0.238)
N	1519	1437	1519	1519	1437	1519
R^2	0.257	0.031	0.037	0.289	0.048	0.053

Note. CR = Conversion Rate; CP = Channels Proliferation; SKUP = SKU Proliferation; KOLP1= KOL's Popularity; KOLP2 = KOL's Professionalism; KOLFF = KOL's female fans ratio; RT = Response Time; MCN = Multi-Channel Network.

Note. Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.2.3. First-stage moderated mediation analysis

Next, we report further results related to Hypothesis 3a-5b, which predicts the first-stage moderated mediation effects. Moderated mediation exists when the value of the indirect effect is conditional on the value of the moderator variable; it is tested by calculating the "conditional indirect effect" (CIE) at different values of the moderator variable and computing whether or not the difference between these CIEs is statistically significant. Thus, we tested this hypothesis by calculating the CIEs at different values of our moderator variables (KOL's popularity, professionalism, and attractiveness to female fans) and checking the difference between these CIEs [136].

Table 6 presents the results of the first-stage moderated mediation. In the moderated mediation tests, for channel proliferation and sales volume, the CIEs are 0.024 (S.E.=0.015) and 0.098 (S.E.=0.015) if the KOL's popularity is one standard deviation below the mean versus one standard deviation above the mean, respectively, indicating the significant moderated mediation effect. Similarly, for channel proliferation and average revenue per user, the CIEs are -0.010 (S.E.=0.009) and 0.031 (S.E.=0.008) if the KOL's popularity is one standard deviation below the mean versus one standard deviation above the mean, respectively, indicating the moderated mediation effect. Thus, we find support for Hypothesis 3a. In the moderated mediation tests, for SKU proliferation and sales volume, the CIEs are -0.006 (S.E.=0.005) and 0.037 (S.E.=0.006) if the KOL's popularity is one standard deviation below the mean versus one standard deviation above the mean, respectively, indicating the significant moderated mediation effect. Similarly, for SKU proliferation and average revenue per user, the CIEs are 0.005 (S.E.=0.006) and 0.035 (S.E.=0.009) if the KOL's popularity is one standard deviation below the mean versus one standard deviation above the mean, respectively, indicating the moderated mediation effect. Thus, we find support for Hypothesis 3b.

In the moderated mediation tests, for channel proliferation and sales volume, the CIEs are 0.019 (S.E.=0.003) and 0.047 (S.E.=0.010) if the KOL's professionalism is one standard deviation below the mean versus one standard deviation above the mean, respectively, indicating the significant moderated mediation effect. Similarly, for channel proliferation and average revenue per user, the CIEs are 0.006 (S.E.=0.008) and 0.015 (S.E.=0.005) if the KOL's professionalism is one standard deviation below the mean versus one standard deviation above the mean, respectively, indicating the moderated mediation effect. Thus, we find support for Hypothesis 4a. In the moderated mediation tests, for SKU proliferation and sales volume, the CIEs are 0.012 (S.E.=0.003) and 0.038 (S.E.=0.011) if the KOL's professionalism is one standard deviation below the mean versus one standard deviation above the mean, respectively, indicating the significant moderated mediation effect. Similarly, for SKU proliferation and average revenue per user, the CIEs are 0.008 (S.E.=0.005) and 0.027 (S.E.=0.007) if the KOL's professionalism is one standard deviation below the mean versus one standard deviation above the mean, respectively, indicating the moderated mediation effect. Thus, we find support for Hypothesis 4b.

In the moderated mediation tests, for channel proliferation and sales volume, the CIEs are 0.039 (S.E.=0.013) and 0.013 (S.E.=0.008) if the KOL's female fans proportion is one standard deviation below the mean versus one standard deviation above the mean, respectively, indicating the significant moderated mediation effect. Similarly, for channel proliferation and average revenue per user, the CIEs are 0.014 (S.E.=0.005) and 0.009 (S.E.=0.005) if the KOL's female fans proportion is one standard deviation below the mean versus one standard deviation above the mean, respectively, indicating the moderated mediation effect. Thus, we find support for Hypothesis 5a. In the moderated mediation tests, for SKU proliferation and sales volume, the CIEs are 0.025 (S.E.=0.009) and 0.018 (S.E.=0.011) if the KOL's female fans proportion is one standard deviation below the mean versus one standard deviation above the mean, respectively, indicating the significant moderated mediation effect. Similarly, for SKU proliferation and average revenue per user, the CIEs are 0.024 (S.E.=0.006) and 0.017 (S.E.=0.010) if the KOL's female fans proportion is one standard deviation below the mean versus one standard deviation above the mean, respectively, indicating the moderated mediation effect. Thus, we find support for Hypothesis 5b.

4.2.4. Second-stage moderated mediation analysis

Then, we report results related to Hypothesis 6, which predicts the second-stage moderated mediation effects of the KOL's quote. Again, we tested this hypothesis by calculating the CIEs at different values of our moderator variables (KOL's quote) and checking the difference between these CIEs [136].

Table 7 presents the results of the second-stage moderated mediation. In the moderated mediation tests, for channel proliferation and sales volume, the CIEs are 0.030 (S.E.=0.019) and 0.018 (S.E.=0.014) if the KOL's quote is one standard deviation below the mean versus one standard deviation above the mean, respectively, indicating the moderated mediation effect. Similarly, for channel proliferation and average revenue per user, the CIEs are 0.027 (S.E.=0.010) and 0.012 (S.E.=0.008) if the KOL's quote is one standard deviation below the mean versus one standard deviation above the mean, respectively, indicating the moderated mediation effect. For SKU proliferation and average revenue per user, the CIEs are 0.040 (S.E.=0.026) and 0.012 (S.E.=0.019) if the KOL's quote is one standard deviation below the mean versus one standard deviation above the mean, respectively, indicating the moderated mediation effect. Thus, we find support for Hypothesis 6.

Table 6 The conditional indirect effect of Channel/SKU proliferation on sales performance through conversion rate moderated by KOL's popularity, professionalism, and attractiveness to female fans

		Sales Volume (SV)					Average Revenue Per User (ARPU)				
Independent variable	**Moderator**	**Level**	**Conditional indirect effect**	**Boot *SE***	**Boot 95% CI**		**Level**	**Conditional indirect effect**	**Boot *SE***	**Boot 95% CI**	
					LL	**UL**				**LL**	**UL**
Channel proliferation	KOL's popularity	Low	0.024	0.015	0.005	0.047	Low	-0.010	0.009	-0.025	0.008
		Mean	0.049	0.011	0.013	0.067	Mean	0.011	0.004	0.005	0.019
		High	0.098	0.015	0.036	0.116	High	0.031	0.008	0.009	0.057
	KOL's professionalism	Low	0.019	0.003	0.015	0.054	Low	0.006	0.008	-0.004	0.024
		Mean	0.033	0.009	0.017	0.054	Mean	0.011	0.004	0.002	0.021
		High	0.047	0.010	0.021	0.085	High	0.015	0.005	0.004	0.029
	KOL's female fans	Low	0.039	0.013	0.016	0.065	Low	0.014	0.005	0.005	0.026
		Mean	0.028	0.009	0.015	0.045	Mean	0.012	0.006	0.001	0.019
		High	0.013	0.008	-0.008	0.037	High	0.009	0.005	-0.002	0.015
SKU proliferation	KOL's popularity	Low	-0.006	0.005	-0.026	0.010	Low	0.005	0.006	-0.006	0.032
		Mean	0.016	0.003	0.006	0.029	Mean	0.014	0.005	0.006	0.031
		High	0.037	0.006	0.010	0.082	High	0.035	0.009	0.008	0.082
	KOL's professionalism	Low	0.012	0.003	0.000	0.036	Low	0.008	0.005	0.002	0.019
		Mean	0.025	0.010	0.011	0.043	Mean	0.017	0.004	0.007	0.033
		High	0.038	0.011	0.017	0.071	High	0.027	0.007	0.008	0.060
	KOL's female fans	Low	0.025	0.009	0.010	0.042	Low	0.024	0.006	0.009	0.042
		Mean	0.022	0.008	0.009	0.034	Mean	0.020	0.009	0.001	0.033

High	0.018	0.011	-0.009	0.030	High	0.017	0.010	-0.007	0.025

Note. Bootstrap resample = 5000. Conditions for moderator (investment in radical innovation) are the mean and plus/minus one standard deviation from the mean.SE = standard error; CI = confidence interval; LL = lower limit; UL = upper limit. We reported Bias-Corrected and accelerated (BCa) confidence intervals for each parameter estimated in the moderated mediation model.

Table 7 The conditional indirect effect of Channel/SKU proliferation on sales performance through conversion rate moderated by KOL's quote (H6)

		Sales Volume (SV)					Average Revenue Per User (ARPU)				
Independent variable	**Moderator**	**Level**	**Conditional indirect effect**	**Boot *SE***	**Boot 95% CI**		**Level**	**Conditional indirect effect**	**Boot *SE***	**Boot 95% CI**	
					LL	**UL**				**LL**	**UL**
Channel proliferation	KOL's quote	Low	0.030	0.019	0.007	0.069	Low	0.027	0.010	0.009	0.044
		Mean	0.023	0.018	-0.008	0.049	Mean	0.019	0.009	-0.001	0.031
		High	0.018	0.014	-0.014	0.038	High	0.012	0.008	-0.003	0.020
SKU proliferation	KOL's quote	Low	0.005	0.008	-0.012	0.015	Low	0.040	0.026	0.011	0.073
		Mean	0.004	0.003	-0.013	0.013	Mean	0.023	0.020	-0.010	0.046
		High	0.003	0.006	-0.017	0.009	High	0.012	0.019	-0.008	0.026

Note. Bootstrap resample = 5000. Conditions for moderator (investment in radical innovation) are the mean and plus/minus one standard deviation from the mean.SE = standard error; CI = confidence interval; LL = lower limit; UL = upper limit. We reported Bias-Corrected and accelerated (BCa) confidence intervals for each parameter estimated in the moderated mediation model.

4.3 Robustness test

We further ran robustness checks to confirm the overall validity of our main findings. First, we used the gross merchandise value (GMV) as an alternative dependent variable of sales volume and the average transaction value (ATV) as an alternative dependent variable of ARPU. GMV is the total value of merchandise sold over the live stream [137-138]. ATV is a consumer's average RMB amount in a single transaction in the live stream [139]. Both GMV and ATV have been extensively used to measure the sales performance of live streams in e-commerce [138]. We used the log-transformed value of each variable in the robustness test. Second, we ran a Tobit regression model on the original sample rather than a linear regression model. Considering that the dependent variable in the data was observed only within a certain range of values (above zero), the sample was left-censored, which was appropriate for the Tobit model.

Models (1) and (2) in Table 8 confirm the main effect of channel proliferation and SKU proliferation on GMV and ATV using the Tobit model, indicating the robustness of the main results.

Table 8 Robustness Test. Tobit regressions.

Variables	(1) Tobit model lnGMV	(2) Tobit model lnATV
CP	0.103**	0.035***
	(0.042)	(0.011)
SKUP	0.373***	0.035**
	(0.050)	(0.014)
Controls	Yes	Yes
Category FE	Yes	Yes
MCN FE	Yes	Yes
Constant	Yes	Yes
N	1519	1519
Wald Test	237.333***	77.509***

Note. GMV = Gross Merchandise Value; ATV = Average Transaction Value; CP = Channels Proliferation; SKUP = SKU Proliferation; MCN = Multi-Channel Network.
Note. Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5. Discussion

This study uses Taobao Live as a representative research context to examine the relationship between proliferation, conversion rate, and live streaming commerce sales performance. In addition, this study also explores the factors affecting the above relationship, including the KOL's popularity, professionalism, attractiveness to female fans, and quote.

Based on a sample of 1,519 live streams from 1st to 31st December 2021, our empirical results show that the conversion rate partially mediates the relationship between channel/SKU proliferation and live stream sales performance.

The findings are consistent with prior studies suggesting that live streamers use more interaction channels to more effectively reach customers [91]. Moreover, our results indicate that channel/SKU proliferation's positive effects on the conversion rate are strengthened when the KOL are popular and professional but weakened when the KOL has a larger female fans proportion. Still, our results indicate that the positive effect of the conversion rate on sales performance is weakened when the KOL asks for a higher quote to present a live stream. The findings suggest theoretical contributions and guide for retailers to select the "right" KOL in live streaming commerce.

5.1 Theoretical contributions

Our study presents important theoretical contributions to the e-commerce literature. First, we identify the underlying mechanism of how proliferation promotes sales performance in live streaming commerce. Although prior literature has stated that proliferation is a major feature of live streaming commerce, especially compared to traditional online shopping, the mechanism of the above effect stays unanswered. Our study proposes that the conversion rate to purchases plays a mediating role in the relationship between channel/SKU proliferation and sales, indicating that proliferation increases sales through converting live stream viewers into practical purchases.

Second, we examine the positive effect of channel proliferation on the conversion rate of live streams, reconciling the gap in e-commerce literature, which overlooks the importance of increasing interaction channels with customers. Prior literature proposes that channel proliferation increases viewers' engagement with the KOL [44], brands, and retailers [140]. Our findings are consistent with prior literature stating that customer engagement could increase sales [141]. Our study, also as a step further, stresses the importance of channel proliferation in live streaming commerce to attract consumers to convert to purchases [142], therefore creating more value for retailers [143]. We also examine the positive effect of SKU proliferation on the conversion rate of live streams.

Although the important role of SKU proliferation is already noted, some previous studies stay skeptical of it due to its potential distraction to customer decision-making [56]. Our study, on the contrary, examines that SKU proliferation increases the conversion rate and the subsequent sales performance, consistent with the literature stream, which stresses that SKU proliferation could attract more customers [144] to convert to purchases [145].

Third, our study explores the boundary conditions of the live streaming commerce proliferation-sales relationship in the context of KOLs as streamers to build a more complete and finer-grained framework. The contingency factors reflect the main indicators retailers should consider when selecting a KOL in live streaming commerce. Specifically, the findings on the moderating effect of KOL's popularity and professionalism on the relationship between channel/SKU proliferation and the conversion rate of live streams are consistent with prior studies highlighting KOL's role in attracting consumers to online promotion [86]. Meanwhile, the finding on the moderating effect of KOL's quote on the relationship between the conversion rate and live stream sales is noteworthy. This finding is also consistent with prior studies that hold a skeptical view of hiring KOL [110], especially considering the constrained budget; it is not very reasonable to hire KOLs with a high quote unless the KOL's popularity/professionalism persuades consumers to convert into purchases could mitigate the KOL's high cost.

5.2 Practical implications

Our findings have important implications for KOLs, advertisers, retailers, live streaming platforms, and other market participants. For advertisers and retailers, our results provide further evidence of the importance of picking popular and professional KOLs to promote their products. Our results also suggest that KOLs and those live streamers use their fans' flow and understand the preferences of fan groups from various channels to realize the value of the live streaming traffic. At the same time, live streamers should fully use Weibo, the Wechat official account, Xiaohongshu, and other social platforms to release high-quality content and strengthen the interaction with fans to enhance user viscosity. The most important thing is that live streamers should constantly strengthen their professional skills, such as commodities involvement and bargaining power, and learn to provide various services through text, short videos, and live. Therefore, MCN institutions should first strengthen the professional training and management of KOLs and pay attention to the cultivation and retention of middle-level KOL streamers. At the same time, MCN institutions, as a bridge between live streaming KOL and retailers, should encourage KOLs to establish differentiated personal images and create unique personalized content to improve and sustaining personal reputation constantly.

5.3 Limitations and future research

This study can be further improved from the following aspects. First, this paper explores the moderating effect of KOL's popularity, professionalism, attractiveness to fans, and quote in live streaming commerce. While recent studies point out that KOL has many features, future research could further explore the effect of KOL's features in the context of live streaming commerce, for instance, KOL's attractiveness to young fans. Second, this study mainly focuses on China as the research context, and the external generalizability may be limited. Future research could further explore live streaming commerce in other countries. Third, we use several alternative measures to our dependent variable to establish our study's robustness. Future research can further explore more sales performance variables, such as the proportion of returned products, repeat purchase behavior, and other indicators of particular importance in the live streaming commerce context.

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