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Differentiation or Homogenization? Impacts of Product Diversity on Jade Live-streaming Performance

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Abstract

With its exponential growth in recent years, live-streaming e-commerce is emerging as an irreplaceable major distribution channel for product sales, particularly for non- standard products like jade. Although recent research has focused on exploring ways to enhance the performance of live broadcasts, the product selection strategy has often been overlooked. In this paper, we investigate the impacts of product diversity on live-streaming performance, including Gross Merchandise Volume (GMV) and fan growth. Based on an analysis of 1,556 different live broadcasts on Douyin, our empirical results indicate that: (1) Product type diversity negatively influences both GMV and fan growth; (2) Product price diversity enhances GMV but detracts from fan growth; (3) Product popularity diversity positively impacts both GMV and fan growth; and (4) Product visibility diversity negatively affects both GMV and fan growth; and (5) The impact of product diversity varies among different streamers, influenced by factors such as their popularity, live broadcast experience, and overall performance. These findings highlight the significance of product diversity in live-streaming operation management, providing sellers and streamers with key managerial insights to optimize their product selection strategy.

Keywords: Live-streaming e-commerce, Product diversity, Gross Merchandise Volume, Fan growth, Non-standard products.

Contents

1 Introduction

Live-streaming e-commerce, a combination of the live-streaming and the online shopping, has experienced explosive growth in recent years. As of June 2023, the live-streaming e-commerce user base in China has grown to 530 million, according to iResearch's report for that year (iResearch, 2023). This statistic clearly demonstrates that live-streaming has evolved into a crucial platform for online shoppers seeking to make purchases. In 2023, China's live-streaming e-commerce market size reaches 4.9 trillion RMB, which is 35.2% more than the market size in 2022. Different from traditional online shopping, live-streaming e-commerce presents a unique opportunity for sellers to conduct oral product introductions or try-on shows in real-time. In other words, live-streaming provide chances for consumers to see the product in real-time, interact with the streamer, and get to know more about the product information (Feng et al., 2024).

Live-streaming has established a more direct and interactive connection between manufacturers and consumers comparing with traditional reselling channels. As a result, it provides a novel and dynamic platform for non-standard products that are traditionally difficult to sell on conventional e-commerce platforms (Qi et al., 2022). These unique items, such as antiques, paintings, and jade, each possess distinct characteristics and values that can be challenging to convey through static images or textual descriptions alone. For instance, the value of jade is determined by a multitude of factors, including its unique variety, water content (or transparency), color, craftsmanship, and even the presence of flaws, which can significantly enhance or detract from its overall worth. Live-streaming enables consumers to clearly see and appreciate these intricate attributes of a jade item in real-time, allowing for a more comprehensive understanding of its quality and value instead of stepping into a store personally. This immersive experience makes live-streaming a particularly beneficial platform for jade sales, as buyers can make more informed decisions based on a detailed examination of the product. In 2018, jade live-streaming sales accounted for 87% of total sales in the sector (DuiZhuang FeiCui and China Gemstone Association, 2019), and by 2020, the online Gross Merchandise Volume (GMV) of jade trading reached 230 billion RMB (DuiZhuang FeiCui and China Gemstone Association, 2020). Since then, live-streaming has become a major online channel for non-standard product sales, making the question of how to increase live broadcast sales a worthwhile pursuit for businesses in this sector.

Extensive research has investigated the factors that impact live-streaming performance, typically categorized into two main groups the characteristics of the streamers and the attributes of the products being promoted (Bharadwaj et al., 2022; Chen et al., 2023; Cheng et al., 2019). However, these studies have mainly concentrated on the streamers' attributes, such as their number of fans and gender, there remains a notable lack of understanding regarding the impacts of the products' features on live broadcast performance. Additionally, prior studies have mainly focused on standard products and overlooked non-standard products, which has undergone a rapid growth in recent years. To address these gaps, this study aims to explore the specific impact of product diversity on jade live-streaming performance. Figure 1 illustrates broadcasts with varying levels of product diversity. Specifically, Figure 1(a) exhibits greater diversity in product types and prices, while Figure 1(b) shows a more concentrated range of product types and prices within the live streaming room.

(a) High product diversity (b) Low product diversity

Figure 1. Live-Streaming E-commerce with Different Product Diversity

Theoretically, there exist competing tensions that may influence the implications of product diversity on live-streaming performance, particularly for non-standard products. On the one hand, given the inherent diversity among consumers and their distinct tastes and preferences, offering a wider array of products is more likely to cater to the needs of a broader range of consumer segments (Ulu et al., 2012). This, in turn, leads to an increase in the number of viewers tuning in to the live broadcast, as individuals are drawn to the diverse selection of products being offered. Ultimately, this approach enhances the overall appeal and attractiveness of the live broadcast, fostering a larger and more engaged audience. On the other hand, while a broad range of products can enhance the appeal of a live broadcast,offering a more focused selection can also be advantageous in attracting a specific consumer segment. This approach allows live streamers to concentrate their efforts on meeting the unique needs and preferences of a particular group of consumers. By tailoring their product offerings to align with the interests and desires of this targeted audience, streamers can create a stronger connection and sense of relevance, ultimately leading to a higher conversion rate. In this research, we aim to empirically examine the impact of product diversity on live broadcast performance in the context of live-streaming e-commerce, answering the question of whether it is better to offer a diverse range of products in live-streaming or to offer specific products.

To answer this question, we collect data from *Daduoduo.com*, a professional live-streaming e-commerce data analysis platform. Considering the product's intrinsic characteristic and market performance, we categorized product diversity into four types: product type diversity, product price diversity, product popularity diversity, and product visibility diversity. Our empirical findings have yielded several noteworthy insights. Firstly, greater product type diversity enhances live broadcast performances, while higher product price diversity results in increased GMV but decreased fan growth. Secondly, higher product popularity diversity improves live broadcast performances, whereas greater product visibility diversity leads to poorer live broadcast performances. Thirdly, streamers' attributes play a moderating role in the correlation between product variety and the performance of live-streaming. These findings provide practitioners, particularly streamers and sellers, with practical insights that can help in developing optimal product selection strategies to enhance product sales and boost consumer engagement.

The structure of this paper is as follows. Section 2 provides a review of relevant literature. In Section 3, our hypotheses are formally proposed. Section 4 explains the research context and details the empirical methods used. Section 5 outlines the findings and includes robustness checks. Lastly, Section 6 provides a conclusion to the paper.

2 Related Literature

In recent years, the live-streaming e-commerce industry is booming, and this emerging business model has also aroused wide attention in the academic community. Current studies on live-streaming e-commerce primarily concentrates on consumer behavior. First of all, from the perspectives of consumers, streamers, and live broadcast platforms perspectives, scholars explored the factors that affect consumers' viewing and engagement behaviors. From the individual characteristics of consumers, the motivations for users to watch live broadcasts mainly include interactivity (Kang et al., 2021; Li et al., 2021) , entertainment (Liu et al., 2020), and utilitarian (Wongkitrungrueng and Assarut, 2020). Besides, the credibility and expertise of the streamer(Zhao et al., 2023), as well as the design features of the live-streaming platform (Xiao et al., 2022), are also considered as important factors to enhance user experience and attract viewers. Moreover, operational characteristics of live-streaming such as the frequency and length of live broadcasts also have a significant impact on audience engagement Zeng et al. (2020). In addition, some scholars also pay attention to consumers' behavior of giving tips or virtual gifts during live broadcast. This kind of study not only discusses the feasibility of "pay what you want" pricing strategy in live broadcasting, but also analyzes the driving factors behind it. For instance, a study by Lu and Chen (2021) demonstrates a strong positive relationship between the viewership numbers during live broadcasts and streamers' earnings. Lin et al. (2021), from the perspective of streamers' emotions, found that the positive emotions of streamers can effectively convey to consumers and stimulate their willingness to give virtual gifts. In addition, Guan et al. (2022) pointed out the important role of information technology factors and cultural characteristics.

More relevant to this paper are studies that explore consumer purchasing behavior during live broadcasts. These studies have analyzed the factors affecting consumers' purchase intention from multiple perspectives such as platforms, streamers, live content, and products (Guo et al., 2021; Zheng et al., 2023; Zeng et al., 2020). For instance, Zheng et al. (2023) demonstrates that factors such as the interactivity and social presence of live-streaming content, the expertise and trustworthiness of streamers, and the appropriate level of stimulation for consumers all play crucial roles in influencing consumers' purchasing intentions. Xu et al. (2023) emphasized the key role of motivational factors (i.e., information seeking, perceived serendipity, relaxation, and symbolic motivation), opportunity factors (i.e., time availability, platform empowerment, and e-word of mouth), and ability factors (i.e., self-efficacy) in shaping consumers' purchase intention. However, it is worth noting that most of the current research on consumer purchasing behavior relies on data obtained from questionnaires. In contrast, there is a scarcity of studies on actual consumer purchasing behaviors in live-streaming e-commerce, with only a handful of scholars incorporating real transaction data into their research. For example, by using 99,451 sales pitches on a live-streaming e-commerce platform and cross-referencing them with actual sales transactions, Bharadwaj et al. (2022) demonstrated that each emotional display, including happiness, uniformly showed a negative U-shaped effect on sales over time. Chen et al. (2023) examined the data of live-streaming shows on Alibaba's live-streaming platform, and pointed out that the number of fans of the streamer, the time arrangement of the live broadcast (i.e., live broadcast duration, whether it is on weekends or not), and product selection (product quantity and price level) have important impacts on the sales performance and the growth of fans of live broadcast. Yang et al. (2023) pointed out that the depth of product assortment being offered and the gender of the streamers in live broadcasts play a crucial role in determining the sales performance of the live-streaming. Consequently, the product selection strategy of live broadcast has an important impact on live broadcast performance and is one of the key factors for the success of live-streaming e-commerce. However, the current relevant studies mainly focus on the impact of product quantity and price level on live broadcast perfor-

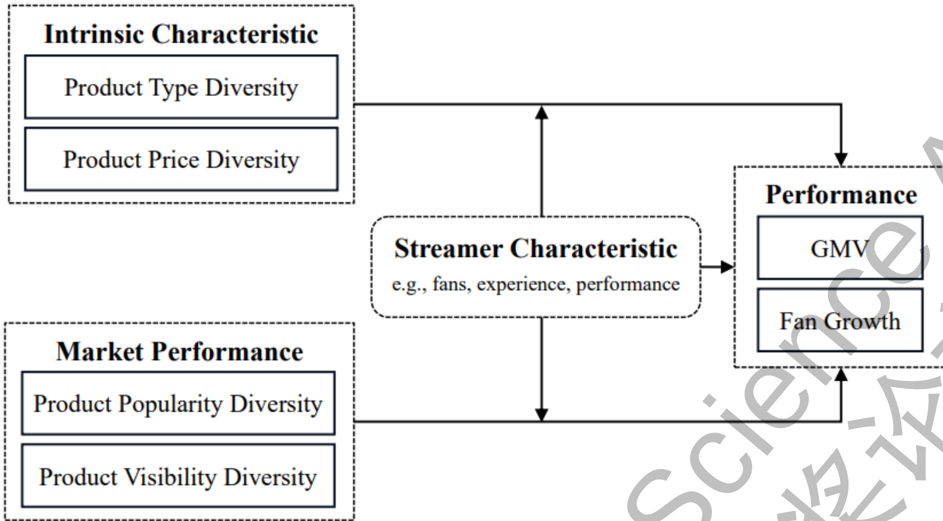

Figure 2. Research Framework

mance and ignore the impact of product differentiation. In the scenario of brick-and-mortal stores, the research found that differentiated product layout strategy plays a crucial role in increasing sales (Dellaert et al., 1998; Dhar et al., 2001; Messinger and Narasimhan, 1997). As an emerging retail model, live-streaming e-commerce may be different from traditional retail in its operational strategy and consumer behavior. Therefore, it remains to be further studied whether product differentiation still has this effect under the live-streaming e-commerce structure. In addition, these studies mainly focus on standard products, while the non-standard products such as jade are still not been studied.

To fill these research gaps, we focus on jade live-streaming e-commerce. From the perspective of product selection strategy, this study explores the effect of product diversity on live-streaming performance, including the short-term (i.e., GMV) and long-term (i.e., fan growth) performance. Specifically, we analyze the impacts of product type diversity, product price diversity, product popularity diversity, and product visibility diversity on GMV and fan growth, taking into account both the product's intrinsic characteristics and its market performance.

3 Theory and Hypothesis Development

From the perspective of a product's intrinsic characteristics and market performance, this paper examines the specific effects of product type diversity, product price diversity, product popularity diversity, and product visibility diversity on live-streaming performance, including the short-term (GMV) and long-term (i.e., fan growth) performance (see more details in Figure 2).

3.1 Impacts of diversity in product's intrinsic characteristic

Diversification of a product's intrinsic characteristic emphasizes the differentiation based on the inherent characteristics or attributes of the product itself.Specifically, this refers to the differentiation in the types and prices of products showcased and recommended during live broadcasts. A live broadcast that focuses on the diversity of its product's intrinsic characteristic can offer a wide range of product types and cover various price ranges, thereby meeting the preferences of various consumer groups. Numerous studies in marketing, psychology, and other disciplines have demonstrated that diversification-seeking behavior is a significant characteristic of consumers when purchasing products (McAlister, 1982; Liu et al., 2015). This pursuit of diversification is manifested not only in the quest for varied intrinsic product characteristics but also in the selection of different types of retailers (Ratner and Kahn, 2002; Mohan et al., 2012; Vakeel et al., 2021). In the context of brick-and-mortar stores, product diversification has been proven to positively impact consumers' purchasing behavior in various ways, including increasing consumption amounts and purchase quantities (Sharma et al., 2010; Kahn and Wansink, 2004; Sarantopoulos et al., 2019). Additionally, research in the retail industry indicates that changes in the number of product types directly affect consumers' purchasing behavior. Notably, a decrease in product types has a significant negative impact on consumers' purchase frequency and quantity Borle et al. (2005); Sloot and Verhoef (2008). Therefore, we propose the following hypotheses:

Hypothesis 1 (H1): Product type diversity positively affects live-streaming performance.

Hypothesis 2 (H2): Product price diversity positively affects live-streaming performance.

3.2 Impacts of diversity in product's market performance

Product market performance diversification is another crucial strategy, emphasizing that the differentiation characteristics of a product stem from its actual performance in the market. Specifically, a product's market performance is typically evaluated based on its popularity and visibility.

Product popularity serves as a key indicator to measure the extent of consumer demand, reflecting the market's attention towards a particular product or service (Fernando and Aw, 2023; Henard and Szymanski, 2001), and is generally quantified by sales volume. For the live broadcasts, although the traffic is not directly equivalent to sales, it is an important basis for sales, without sufficient traffic support, the sales of the broadcast room is out of the question (Lu and Chen, 2021). In practice, the products with more popularity can often attract more viewers and potential consumers into the live broadcast. Therefore, streamers usually choose to hang out some high-traffic products in order to attract consumers to attract consumers to click on the page and increase the overall traffic of the live broadcast to have a higher exposure of other products. Besides, products with lower popularity better meet the needs of different consumer segments. Therefore, through the combination of popular and niche products, more consumer segments' needs can be covered;

those more popular products also bring more sales opportunities for the less popular products in the live broadcast. Previous studies have found out that products with high popularity not only perform well in the market and have high sales volume, but also tend to have positive spillover effects on their related products (such as other products from the same manufacturer or seller) (Liang et al., 2019). This means that a greater diversity of product popularity not only can meet diverse consumer needs, but also significantly improve the performance of low-popularity products in live-streaming through the spillover effect it caused. On the contrary, products within the same classification (i.e., jade) that share similar popularity tend to exhibit similarities, ultimately leading to homogenized competition. As a result, they engage in competition without achieving notable performance improvements. Therefore, we propose the following hypothesis:

Hypothesis 3 (H3): Product popularity diversity positively affects live-streaming performance.

Product visibility diversity serves as a crucial indicator to gauge the level of activity and the extent to which a product is visible to consumers in the market. It can be measured in a variety of ways, such as the number of the product's exposure through advertisements, the frequency of mentions on social media, etc. In this article, we define it as the number of live broadcasts associated with the product. Zhao (2023) noted that when brand exposure is low and unfamiliar to people, an increase in exposure can attract attention to the brand and foster a sense of trust. However, when exposure becomes excessive, people may become disinterested and develop resistance to the brand. Similarly, when product exposure reaches excessive levels, it results in an "over-exposure" situation, leading to a decline in attention. This not only diminishes consumers' willingness to enter the broadcast room but also suppresses their desire to purchase. In reality, "over-exposed" products not only provoke consumer resistance to the product itself but also tend to cause negative spillover effects on related products, which has a negative impact on the overall performance of the live broadcast. Accordingly, we propose the following hypothesis:

Hypothesis 4 (H4): Product visibility diversity negatively affects live-streaming performance.

4 Data and Methodology

4.1 Data

Data collecting. In this paper, we focus on the jade live broadcasts on Douyin, a dominant technical service platform in China's live-streaming e-commerce industry. Specifically, the samples used in our research cover the top 700 jade live broadcasts in weekly sales on Douyin from March 17 to April 6, 2024.

We collect these data from *Daduoduo.com* (more details shown in Figure 3), which is the leading technical service platform in live-streaming e-commerce. Till November 2023, Dadoduo has

Figure 3. Screenshot of *Daduoduo.com*

served more than 3 million users of various roles, and has 10 million daily big data monitoring capabilities. By utilizing a Python-based crawler, we systematically collected detailed information from these live broadcasts, encompassing three main areas: (1) the basic information of the broadcast room, including the name of the broadcast, precise timing, duration, traffic composition during the broadcast, person-time, total number of viewers, as well as the number of new fans gained through this specific live broadcast; (2) details of the streamers, comprising their name, total number of accumulated fans, count of likes received on their content, level of experience in live-streaming, and historical performance metrics across previous broadcasts; and (3) detailed information of recommended products, such as product links, respective names, offered prices, sales amount, and total sales generated specifically during this live broadcast. Additionally, we gathered data on the historical sales amount and overall sales performance of each product, providing a comprehensive view of their market performance.

Data cleaning. We conducted a thorough data cleansing process. To begin with, we delete the data of the live broadcasts where the information of the streamer and the broadcast time are completely repeated to avoid data redundancy. Secondly, we eliminate invalid broadcast rooms, which are unable to conduct subsequent data analysis due to the lack of key information such as product information. After a series of data cleansing, we retained 1,556 valid live broadcasts for analyzing the impact of product diversity on GMV, and 1,529 valid broadcasts for investigating fan growth.

4.2 Variable definitions

Dependent variables. Given that live-streaming e-commerce success as measured by GMV and fan growth (Chen et al., 2023), we measure live-streaming performance by these two evaluation indicators. Specifically, GMV (GMV) refers to the sum of all product sales revenue in a single live broadcast. Fan growth ($FanGrowth$) is the number of new fans gained during the live broadcast.

Independent variables. In this paper, we conceptualize product diversity along two key dimensions: intrinsic product characteristics and market performance, each capturing distinct aspects of product heterogeneity that can shape consumer behavior and outcomes in live broadcasts. The diversity of intrinsic product characteristics consists of two elements: product type diversity ($TypeSD$) and product price diversity ($PriceSD$). Product type diversity reflects the variety in the distribution of products across three predefined categories—special offer, bracelet, and other—within a live broadcast. To align the measurement with the conceptual notion that a more balanced distribution indicates higher diversity, we take the negative value of the standard deviation of product quantities across these categories. This ensures that a more even distribution (e.g., 3,3,3) corresponds to a higher diversity score than an uneven one (e.g., 9,0,0), accurately capturing the desired interpretation of product type diversity, more details see Equation (1). Additionally, we employed Latent Dirichlet Allocation (LDA) to classify product titles into these three categories. Product price diversity captures the variation in price levels and is calculated as the standard deviation of all product prices featured during the broadcast, more details see Equation (2). The diversity of market performance is reflected in product popularity diversity ($SaleSD$) and product visibility diversity ($StreamSD$). Product popularity diversity captures fluctuations in consumer demand and is measured as the standard deviation of individual product sales volumes within the same broadcast over the past week, more details see Equation (3). Product visibility diversity reflects variations in product exposure, quantified as the standard deviation in the number of live broadcasts over the past week that featured these products, more details see Equation (4).

$$TypeSD_{it} = -\sqrt{\frac{\sum_{j=1}^{3}\left(\mathrm{TypeNum}_{jit} - \overline{\mathrm{TypeNum}_{it}}\right)^2}{3}} \tag{1}$$

$$PriceSD_{it} = \sqrt{\frac{\sum_{k=1}^{N}\left(\mathrm{Price}_{kit} - \overline{\mathrm{Price}_{it}}\right)^2}{N}} \tag{2}$$

$$SaleSD_{it} = \sqrt{\frac{\sum_{k=1}^{N}\left(\mathrm{SaleVolume}_{kit} - \overline{\mathrm{SaleVolume}_{it}}\right)^2}{N}} \tag{3}$$

$$StreamSD_{it} = \sqrt{\frac{\sum_{k=1}^{N}\left(\mathrm{Stream}_{kit} - \overline{\mathrm{Stream}_{it}}\right)^2}{N}} \tag{4}$$

where TypeNum_{jit} refers to the number of products in type j for broadcast room i at time t. Price_{kit} represents the price of product k for broadcast room i at time t. SaleVolume_{kit} indicates the sales volume of product k over the past week for broadcast room i at time t. Stream_{kit} captures the number of live broadcasts featuring product k over the past week for broadcast room i at time t.

Control variables. Given that prior studies have identified streamer characteristics as key factors influencing live-streaming performance (Bharadwaj et al., 2022; Chen et al., 2023; Cheng et al., 2019), this study incorporates several streamer-related control variables: Gender (coded as 1 for male and 0 for female), reputation ($Reputation$), popularity ($FanNum$), live broadcast experience ($StreamNum$), live broadcast performance ($TotalSales$), and expertise on jade products ($JadeRatio$). Reputation is an indicator calculated by the platform, incorporating factors such as user evaluations, after-sales service quality, and complaint rates. This indicator reflects the reliability of the products recommended by the streamer, with a maximum score of 5 representing the highest level of reliability. Popularity is measured by the number of fans, representing the total followers accumulated by the streamer prior to the live broadcast. The streamer' s experience is assessed by the total number of live broadcasts they have conducted, while broadcast performance is measured by the total sales revenue generated from these broadcasts within the past 30 days. Finally, expertise in jade products is quantified by the proportion of jade-related products featured in the streamer' s broadcasts over the past 30 days.

Tables 1 and Table 2 provide a detailed overview of the descriptive statistics and correlation coefficients for the key variables used in this study.

Table 1. Descriptive statistics of key variables

Variable	Obs.	Mean	Std. Dev.	Min	Max
LnGMV[a]	1556	10.606	1.309	8.23	15.65
LnFanGrowth[a]	1529	4.867	1.656	0	11.21
LnTypeSD[a]	1556	-2.799	0.682	-4.06	-0.46
LnPriceSD[a]	1556	8.465	2.013	0	15.313
LnSaleSD[a]	1556	3.267	2.144	0	12.375
LnStreamSD[a]	1556	1.265	0.906	0	8.402
Gender	1556	0.232	0.422	0	1
Reputation	1556	4.626	0.322	3.01	5
LnFanNum[a]	1556	11.223	1.537	7.38	17.29
LnStreamNum[a]	1556	3.463	0.654	1.39	5.21
LnTotalSales[a]	1556	15.303	1.381	10.53	18.42
JadeRatio	1556	52.574	29.845	0.05	100

Note: [a] *Natural log transformation.*

Table 2. Correlation matrix of key variables

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) LnGMV	1						
(2) LnFanGrowth	0.46***	1					
(3) LnTypeSD	-0.05*	-0.01	1				
(4) LnPriceSD	0.12***	-0.22***	0.10***	1			
(5) LnSaleSD	0.37***	0.72***	-0.01	-0.23***	1		
(6) LnStreamSD	0.06*	0.09***	-0.02	-0.06*	0.55***	1	
(7) Gender	0.20***	0.29***	-0.03	-0.02	0.24***	-0.03	1
(8) Reputation	-0.07**	-0.00	-0.05	-0.02	-0.01	-0.10***	-0.25***
(9) LnFanNum	0.37***	0.59***	-0.05*	-0.11***	0.64***	0.32***	0.32***
(10) LnStreamNum	-0.19***	-0.53***	-0.00	0.11***	-0.40***	0.15***	-0.10***
(11) LnTotalSales	0.50***	0.52***	0.02	0.06*	0.39***	0.05	0.19***
(12) JadeRatio	-0.01	-0.12***	-0.33***	-0.09***	0.06*	0.12***	-0.04
Variables	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**		
(9) LnFanNum	0.02	1					
(10) LnStreamNum	-0.08***	-0.17***	1				
(11) LnTotalSales	0.07**	0.53***	0.01	1			
(12) JadeRatio	0.06*	0.06*	-0.04	-0.23***	1		

**** p<.01, ** p<.05, * p<.1*

4.3 Empirical model

To explore the impact of product diversity on the live-streaming performance, we rely on a linear regression model shown in Equation (5).

$$\begin{aligned} Y_{it} &= \beta_0 + \beta_1 TypeSD_{it} + \beta_2 PriceSD_{it} + \beta_3 SaleSD_{it} \\ &\quad + \beta_4 StreamSD_{it} + \alpha * Control_{it} + \in_{it} \end{aligned} \tag{5}$$

where i refers to broadcast room. Y represents the dependent variable, which is either GMV (GMV) or fan growth ($FanGrowth$). X represents the control variables, including the $Gender$, $Reputation$, $FanNum$, $StreamNum$, $TotalSales$, and $JadeRatio$. $\in_{it}$ represents the random error term.

Before estimating our main model, we calculated the variance inflation factor (VIF) to assess potential multicollinearity. The results show a mean VIF of 1.81, with individual values ranging from 1.13 to 3.95—well below the critical threshold of 10. Therefore, multicollinearity does not pose a significant concern in this study.

5 Empirical Results

5.1 Effect of product diversity on live-streaming performance

As shown in the Columns (1) and (2) of Table 3, various control variables exhibit significant relationships with live-streaming performance. Notably, male streamers demonstrate higher performance compared to female streamers. Furthermore, the popularity ($LnFanNum$) and live broadcast performance ($LnTotalSales$) of streamers positively influence both GMV and fan growth. However, streamers' live broadcast experience ($LnStreamNum$) exhibits a negative effect on live-streaming performance. Additionally, streamers' expertise on jade ($JadeRatio$) positively impacts GMV, while it negatively affects fan growth.

Building on these control variables, we estimated two models by incorporating the independent variables, with the results presented in Columns (3) and (4) of Table 3. Firstly, the empirical results indicate that product type diversity has a significant negative impact on GMV ($\beta = -0.098$, $p < 0.05$) and fan growth ($\beta = -0.08$, $p < 0.05$). This suggests that offering products with more specific or focused types enhances sales and attracts fans,thereby H1 is rejected. A possible explanation for this effect is that a narrow product selection allows consumers to form clearer expectations about the live content, increasing trust and reducing cognitive overload during the decision-making process. Furthermore, consistent product types align better with consumer preferences and create a sense of brand identity, particularly in niche markets. For example, consumers drawn to a specific product category, such as jade bracelets, may be more likely to follow streamers offering similar products repeatedly. In contrast, an overly diverse product offering may dilute the focus of the broadcast, making it harder for streamers to build a coherent brand image and foster loyal fan engagement.

Product price diversity demonstrates a positive relationship with GMV ($\beta = 0.105$, $p < 0.01$) but a negative impact on fan growth ($\beta = -0.0743$, $p < 0.01$. This indicates that while offering products with diversified prices can increase sales, it may hinder fan growth and long-term live-streaming performance. Thus, H2 is partially supported. The potential reason for product price diversity hindering fan growth could be that offering products with varied prices may introduce uncertainty about future live content, thereby inhibiting fan growth.

Product popularity diversity has significant impacts on both GMV ($\beta = 0.134$, $p < 0.01$) and fan growth ($\beta = 0.406$, $p < 0.01$). Therefore, Hypothesis 3 is supported, which emphasizes the importance of diversified product popularity in live-streaming sales. By offering popular products, live broadcasts can attract consumers and gain more attention for other items, thereby improving performance.

Lastly, product visibility diversity has a significant negative impact on both GMV ($\beta = -0.114$, $p < 0.05$) and fan growth ($\beta = -0.403$, $p < 0.01$), confirming H4. Although increasing product visibility can attract consumers, overexposure or excessive marketing may cause aesthetic fatigue, ultimately diminishing sales and fan acquisition.

Table 3. Results of the impact of product diversity

	(1) LnGMV	(2) LnFanGrowth	(3) LnGMV	(4) LnFanGrowth
LnTypeSD			-.098**	-.08**
			(.042)	(.033)
LnPriceSD			.105***	-.074***
			(.014)	(.011)
LnSaleSD			.134***	.406***
			(.025)	(.02)
LnStreamSD			-.114**	-.403***
			(.045)	(.036)
Gender	.155**	.243***	.1	.084
	(.072)	(.066)	(.072)	(.057)
Reputation	-.447***	-.286***	-.42***	-.27***
	(.09)	(.083)	(.089)	(.071)
LnFanNum	.046**	.345***	.008	.166***
	(.023)	(.021)	(.026)	(.02)
LnStreamNum	-.382***	-1.223***	-.238***	-.671***
	(.043)	(.04)	(.055)	(.044)
LnTotalSales	.469***	.402***	.402***	.276***
	(.025)	(.023)	(.027)	(.021)
JadeRatio	.004***	-.004***	.004***	-.006***
	(.001)	(.001)	(.001)	(.001)
_cons	6.048***	.551	5.459***	2.202***
	(.532)	(.488)	(.537)	(.427)
Observations	1556	1529	1556	1529
R-squared	.32	.649	.35	.748

Standard errors are shown in parentheses

*** $p<.01$, ** $p<.05$, * $p<.1$

5.2 Moderating effect of streamer characteristics

To comprehensively understand the nuanced effects of product diversity and effectively manage the product selection strategy for different types of streamers, we conduct a thorough analysis to ascertain how the influence of product diversity varies among streamers' characteristics, such as popularity, live broadcast experience, and live broadcast performance. By analyzing in this way, we aim to develop more targeted and effective product selection strategies for different streamers. Specifically, we use Equation (6), which incorporates a series of interaction terms into Equation (5), to estimate the heterogeneity in the impact of product diversity:

$$\begin{aligned} Y_{it} \quad = \quad & \beta_0 + \beta_1 TypeSD_{it} + \beta_2 PriceSD_{it} + \beta_3 SaleSD_{it} \\ & + \beta_4 StreamSD_{it} + \gamma_1 TypeSD_{it} * Moderator_{ij} \\ & + \gamma_2 PriceSD_{it} * Moderator_{ij} + \gamma_3 SaleSD_{it} * Moderator_{ij} \\ & + \gamma_4 StreamSD_{it} * Moderator_{ij} + \alpha * Control_{it} + \in_{it} \end{aligned} \tag{6}$$

where $Moderator$ refers to the moderating variables such as the streamers' popularity ($FanNum$), streamers' live broadcast experience ($StreamNum$), and streamers' live broadcast performance ($TotalSales$). More details are shown in the following.

Moderating effect of streamers' popularity. The empirical results presented in Table 4 show that streamers' popularity strengthens the positive relationship between product popularity diversity and live-streaming performance, including both GMV and fan growth. This suggests that popular streamers are better equipped to leverage product popularity diversity, as their increased visibility and consumer trust enable them to introduce multiple trending or well-known products more effectively, thereby enhancing engagement and boosting both sales and fan growth. However, the findings also reveal that streamers' popularity amplifies the negative impact of product visibility diversity on GMV. This suggests that popular streamers may face challenges related to over-exposure, where repeated promotion of the same products can lead to consumer fatigue or psychological aversion. As a result, consumers may perceive the broadcast as lacking novelty, diminishing their interest and willingness to make purchases.

Table 4. Moderating effect of streamer popularity

	(1)	**(2)**
	LnGMV	**LnFanGrowth**
LnTypeSD	-.087**	-.067**
	(.042)	(.034)
LnPriceSD	.101***	-.081***
	(.015)	(.012)
LnSaleSD	.074***	.382***
	(.027)	(.022)
LnStreamSD	.087	-.362***

	(.059)	(.048)
LnTypeSD×LnFanNum	-.025	-.01
	(.03)	(.024)
LnPriceSD×LnFanNum	.035	.04
	(.032)	(.025)
LnSalesSD×LnFanNum	.162***	.095***
	(.034)	(.027)
LnStreamSD×LnFanNum	-.161***	-.038
	(.03)	(.024)
Gender	.039	.05
	(.072)	(.058)
Reputation	-.447***	-.31***
	(.089)	(.071)
LnFanNum	.029	.177***
	(.026)	(.021)
LnStreamNum	-.299***	-.705***
	(.057)	(.045)
LnTotalSales	.406***	.282***
	(.027)	(.021)
JadeRatio	.004***	-.005***
	(.001)	(.001)
_cons	5.477***	2.377***
	(.539)	(.431)
Observations	1556	1529
R-squared	.363	.751

Standard errors are shown in parentheses
*** $p<.01$, ** $p<.05$, * $p<.1$

Moderating effect of streamers' live broadcast experience. Table 5 demonstrates that a streamer's live broadcast experience significantly reduces the negative impact of product type diversity on GMV. This suggests that offering a specific product type is more advantageous for less experienced streamers, as it allows them to build a clear brand identity and meet niche audience expectations. With fewer products to manage, novice streamers can focus more on product details, improving their presentation quality and credibility. In contrast, more experienced streamers benefit from diversifying their product offerings to attract a broader audience. Their accumulated knowledge, skills, and audience rapport enable them to effectively manage varied product categories without confusing their viewers. Additionally, broadcast experience amplifies the negative effect of product price diversity on fan growth. This finding suggests that experienced streamers should avoid offering products with widely varying prices, as this may disrupt audience expectations. Consistent pricing fosters trust and predictability, which are crucial for retaining loyal fans. In contrast, diverse pricing strategies may introduce uncertainty, leading viewers to question the focus of future broadcasts, thereby weakening fan engagement and growth. Lastly, broadcast experience helps mitigate the negative impact of product visibility diversity on fan growth. Experienced streamers likely develop better strategies to manage product visibility, such as balancing promotions and avoiding overexposure, which can prevent audience fatigue. These streamers may also be more adept at rotating product features across multiple sessions, maintaining audience interest without overwhelming viewers with repetitive content.

Table 5. Moderating effect of streamer experience

	(1)	**(2)**
	LnGMV	**LnFanGrowth**
LnTypeSD	-.12***	-.087**
	(.043)	(.034)
LnPriceSD	.111***	-.078***
	(.014)	(.011)
LnSaleSD	.135***	.413***
	(.025)	(.020)
LnStreamSD	-.105**	-.445***
	(.047)	(.038)
LnTypeSD×LnStreamNum	.12***	-.007
	(.029)	(.023)
LnPriceSD×LnStreamNum	-.008	-.043*
	(.032)	(.026)
LnSaleSD×LnStreamNum	-.047	.045
	(.037)	(.029)
LnStreamSD×LnStreamNum	.021	.052*
	(.034)	(.027)
Gender	.089	.087
	(.073)	(.058)
Reputation	-.449***	-.262***
	(.089)	(.071)
LnFanNum	.006	.149***
	(.027)	(.021)
LnStreamNum	-.245***	-.632***

	(.057)	(.045)
LnTotalSales	.389***	.282***
	(.027)	(.021)
JadeRatio	.004***	-.006***
	(.001)	(.001)
_cons	5.698***	2.192***
	(.544)	(.432)
Observations	1556	1529
R-squared	.357	.751

Standard errors are shown in parentheses

**** p<.01, ** p<.05, * p<.1*

Moderating effect of streamers' live broadcast performance. The results in Table 6 show that streamers' live broadcast performance significantly enhances the positive impact of product popularity diversity on both GMV and fan growth. Streamers with strong performance are better positioned to capitalize on popular products, as their credibility attracts more traffic and boosts engagement. By effectively promoting trending products, these streamers maintain audience interest and drive both sales and fan acquisition. However, higher performance also amplifies the negative effect of product visibility diversity, suggesting that successful streamers are more prone to over-exposure. Frequent promotion of the same products may lead to viewer fatigue, reducing audience engagement. To mitigate this, high-performing streamers must balance product visibility by rotating featured items and introducing new content. Lastly, live broadcast performance mitigates the negative impact of product price diversity on fan growth. High performance streamers are better equipped to align product prices with audience expectations, attracting and retaining specific fan segments. By focusing on targeted price tiers, they can reduce uncertainty about future broadcasts, fostering long-term fan loyalty.

Table 6. Moderating effect of streamer performance

	(1)	**(2)**
	LnGMV	**LnFanGrowth**
LnTypeSD	-.072*	-.083**
	(.043)	(.034)
LnPriceSD	.101***	-.074***
	(.014)	(.011)
LnSaleSD	.086***	.394***
	(.026)	(.021)
LnStreamSD	-.013	-.376***

	(.048)	(.039)
LnTypeSD×LnTotalSales	-.024	.013
	(.028)	(.022)
LnPriceSD×LnTotalSales	.034	.057**
	(.031)	(.025)
LnSaleSD×LnTotalSales	.22***	.051*
	(.038)	(.030)
LnStreamSD×LnTotalSales	-.122***	-.064**
	(.038)	(.030)
Gender	.025	.075
	(.072)	(.058)
Reputation	-.461***	-.273***
	(.088)	(.071)
LnFanNum	.005	.163***
	(.025)	(.020)
LnStreamNum	-.295***	-.688***
	(.056)	(.045)
LnTotalSales	.435***	.282***
	(.028)	(.022)
JadeRatio	.004***	-.006***
	(.001)	(.001)
_cons	5.461***	2.211***
	(.535)	(.429)
Observations	1556	1529
R-squared	.366	.750

Standard errors are shown in parentheses
**** p<.01, ** p<.05, * p<.1*

5.3 Robustness checks

Change the independent variable. To further enhance the robustness of our findings, we conducted an additional check by adjusting the metric used to measure the independent variable, product popularity diversity. Initially, we measured product popularity diversity as the standard deviation of sales volume over the past seven days across different products. However, to ensure that our results are not driven by the specific choice of metric and to provide a more nuanced understanding, we substituted this measure with the standard deviation of sales revenue over the past seven days among products featured within the same live broadcast. The results, presented in Table 7, show that the effects of the four independent variables remain consistent with those reported in Table 3. This consistency across different metrics reinforces the robustness and reliability of our findings, confirming that our conclusions are sound and not dependent on a specific operationalization of product popularity diversity.

Table 7. Evidence from alternative measures of product diversity

	(1) **LnGMV**	**(2)** **LnFanGrowth**
LnTypeSD	-.061	-.029
	(.040)	(.037)
LnPriceSD	.074***	-.142***
	(.013)	(.012)
LnSaleSD	.21***	.079***
	(.017)	(.015)
LnStreamSD	-.158***	.021
	(.036)	(.034)
Gender	.155**	.275***
	(.068)	(.063)
Reputation	-.432***	-.275***
	(.085)	(.079)
LnFanNum	.053**	.287***
	(.024)	(.022)
LnStreamNum	-.289***	-1.171***
	(.043)	(.040)
LnTotalSales	.305***	.383***
	(.027)	(.025)
JadeRatio	.002**	-.006***
	(.001)	(.001)
_cons	5.581***	1.657***
	(.516)	(.478)
Observations	1556	1529
R-squared	.399	.684

Standard errors are shown in parentheses

**** p<.01, ** p<.05, * p<.1*

Additional control variables. To enhance the robustness and reliability of our analysis, we have introduced several additional control variables. *Firstly*, we controlled for whether the live broadcasts occurred on weekends to account for potential time-related effects, as consumer engagement, purchasing behavior, and viewership may vary between weekdays and weekends. By isolating these effects, we ensure that any impact on GMV or fan growth is not merely driven by broadcast timing. As shown in Columns (1) and (2) of Table 8, the results remain consistent with those reported in Table 3, reinforcing the validity of our conclusions. *Secondly*, we incorporated the duration of the live broadcasts as a control variable. Longer broadcasts might increase exposure and engagement, potentially amplifying product sales and fan growth. Controlling for broadcast duration ensures that the observed relationships are not merely a result of varying levels of exposure across sessions. The outcomes, presented in Columns (3) and (4) of Table 8, align with and further strengthen our previous findings, adding additional credibility to our research. *Thirdly*, we included the average shelf duration of products as a control variable. Products with longer shelf durations may benefit from extended visibility, which could influence both consumer interest and purchasing behavior. By controlling for shelf duration, we isolate the impact of other factors, ensuring that the results are not confounded by differences in product exposure time. The findings in Columns (5) and (6) of Table 8 remain consistent with our initial results.

Table 8. Evidence from extra control variables

	(1) LnGMV	(2) LnFanGrowth	(3) LnGMV	(4) LnFanGrowth	(5) LnGMV	(6) LnFanGrowth
LnTypeSD	-.094**	-.078**	-.056	-.032	-.081*	-.072**
	(.042)	(.033)	(.043)	(.033)	(.042)	(.033)
LnPriceSD	.107***	-.073***	.114***	-.064***	.11***	-.07***
	(.014)	(.011)	(.014)	(.011)	(.014)	(.011)
LnSaleSD	.134***	.406***	.144***	.416***	.154***	.418***
	(.025)	(.02)	(.025)	(.02)	(.025)	(.02)
LnStreamSD	-.108**	-.401***	-.13***	-.42***	-.154***	-.427***
	(.045)	(.036)	(.045)	(.036)	(.046)	(.037)
Gender	.092	.08	.12*	.106*	.117	.094
	(.072)	(.057)	(.072)	(.056)	(.072)	(.057)
Reputation	-.43***	-.274***	-.438***	-.29***	-.403***	-.258***
	(.088)	(.071)	(.088)	(.069)	(.088)	(.07)
LnFanNum	.008	.166***	.003	.16***	.009	.169***
	(.026)	(.02)	(.026)	(.02)	(.026)	(.02)
LnStreamNum	-.241***	-.672***	-.253***	-.69***	-.253***	-.679***
	(.055)	(.044)	(.055)	(.043)	(.055)	(.044)
LnTotalSales	.402***	.276***	.373***	.246***	.381***	.263***
	(.027)	(.021)	(.027)	(.021)	(.027)	(.022)

JadeRatio	.004***	-.006***	.004***	-.005***	.004***	-.006***
	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)
Weekend	.153***	.067				
	(.059)	(.047)				
lnDuration			.32***	.355***		
			(.062)	(.049)		
lnProductTime					.258***	.142***
					(.051)	(.04)
_cons	5.464***	2.207***	4.384***	.999**	3.309***	.987*
	(.536)	(.427)	(.572)	(.451)	(.685)	(.546)
Observations	1556	1529	1556	1529	1551	1524
R-squared	.353	.749	.361	.757	.36	.751

Standard errors are shown in parentheses

**** p<.01, ** p<.05, * p<.1*

6 Discussion

This paper examines product selection strategies in jade live-streaming e-commerce, focusing on two dimensions: intrinsic product characteristic diversity and market performance diversity, and analyse their impact on both the GMV and fan growth. The results show that: (1) Product intrinsic characteristic diversity, including product type diversity and product price diversity, has a significant impact on live broadcast performance. To be more specific, product type diversity negatively influences live-streaming performance, as providing specific product types effectively promotes the increase of GMV and fan growth. Nonetheless, the impacts of varied product prices are more intricate. It has a large positive influence on the GMV, but a detrimental effect on the growth of fans. Consequently, offering diversified product prices can effectively promote the increase of product sales,but cannot bring stable audience and subsequently inhibit the increase of fan growth. (2) Product market performance diversity also significantly impacts live-streaming performance. Product popularity diversity positively influences live-streaming performance. This happens because popular products draw more viewers to the live-streaming room. This, in turn, not only improves the sales of less-popular products through a positive spillover effect but also brings a stable audience to the streamer. Conversely, product visibility diversity negatively impacts live broadcast performance. Products with excessively high or low visibility fail to attract viewers, causing negative spillover effects that inhibit sales and fan growth. (3) Streamers' characteristics, including popularity, live broadcast experience, and live broadcast performance, have a moderating effect on the relationship between product diversity and live-streaming performance. Therefore, different streamers should consider their own conditions when selecting products and avoid blindly pursuing product diversity.

6.1 Literature contributions

Our results significantly advance prior research in several important ways. Firstly, this work broadens the scope of extant research on live-streaming e-commerce. Prior literature in this field has heavily relied on subjective questionnaires to explore consumer behaviors in the context of live-streaming e-commerce (Guo et al., 2021; Zheng et al., 2023; Zeng et al., 2020), which may not accurately capture the complexities and nuances of consumer behavior in today's unique and rapidly evolving market. In recent years, a few studies have attempted to address this limitation by exploring consumer behaviors based on real data. However, their focus has primarily been on the characteristics of the streamers themselves, rather than the products being sold. Only a limited number of studies, such as Zheng et al. (2023) and Yang et al. (2023), have specifically focus on the product itself, however, they have largely focused on the quantity and price level of the product. In contrast, we explore the impacts of product diversity on consumer purchasing and following behaviors through real live broadcast data.

Secondly, this study makes a significant contribution to the existing literature on product differentiation strategies. In the traditional bricks-and-mortar economy, product differentiation strategy has long been recognized as a crucial factor affecting the performance of businesses (Dellaert et al., 1998; Dhar et al., 2001; Messinger and Narasimhan, 1997). By emphasizing the importance of product diversity in the context of live-streaming e-commerce, our paper extends the understanding of product differentiation strategies in the digital economy.

Last but not least, by focusing on jade live-streaming, our paper contributes to the broader understanding of how non-standard and high-value items can be successfully marketed and sold through digital platforms.

6.2 Practice contributions

Our findings also provide valuable insights for the platform, sellers, and streamers in formulating effective live broadcast product selection strategies. For live broadcasts that are primarily focused on sales, it is recommended to choose a higher level of product price diversity and product popularity diversity, while keeping product type diversity and product visibility diversity relatively low. This approach allows for a wider range of products to be offered, catering to different consumer preferences and price points, ultimately driving sales. In contrast, for live broadcasts that aim to increase fan growth, it is advisable to select a higher level of product popularity diversity, while keeping product type diversity, product price diversity, and product visibility diversity relatively low. This strategy helps attract a broader audience and foster engagement, as the focus is on offering popular and diverse products without overwhelming viewers with a wide range of prices or excessive product visibility.

For streamers, tailoring product selection strategies is essential for optimizing sales and promoting fan growth. For streamers with a large following, prioritizing greater product popularity diversity while limiting product visibility diversity can sustain viewer interest by leveraging popular products without overwhelming the audience with overexposure. In addition, less experienced streamers may benefit from focusing on specific product types, as a more specialized approach can enhance their credibility and drive sales. However, as streamers gain experience, expanding their product offerings to include a wider variety of types becomes crucial for attracting a more diverse audience and sustaining long-term engagement. To foster fan growth, experienced streamers should emphasize consistent pricing by limiting product price diversity. Predictable pricing helps maintain trust among viewers while higher product visibility diversity allows streamers to keep their audience engaged through frequent exposure to products. High-performing streamers, in particular, should increase product popularity diversity to attract more traffic and enhance sales. However, they must carefully manage product visibility diversity, as excessive promotion of the same products can lead to audience fatigue. To sustain engagement, streamers with stronger performance should balance product visibility with new product offerings. Additionally, by strategically incorporating diverse price points alongside popular products, streamers can cater to different consumer segments and enhance fan loyalty.

6.3 Limitation and future research directions

This study, being one of the pioneering ones to explore the correlation between product diversity and live-streaming success, comes with certain limitations that open avenues for future exploration. We focused solely on a non-standard and high-value product category—the jade. Future study might look at whether different effects are observed for different types of products (e.g., low- and high-value products, standard and non-standard products). Furthermore, further research could also use alternative research methods, such as laboratory experiments, to test our theoretical predictions and, more importantly, to examine the underlying mechanisms through which the product diversity affects consumer behaviors.

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1. 论文的选题来源、研究背景

随着互联网技术的迅猛发展，直播已逐渐成为一种不可或缺的购物方式，广泛渗透到日常生活的各个方面。在直播平台上，消费者可以轻松浏览并购买各种生活物资，无论是日用品还是食品饮料，都应有尽有。然而，仔细观察后不难发现，这些商品中大部分都是标准的工业性商品。这主要是因为直播这种形式能够以直观、快速的方式展示商品的特点和使用效果，从而有效吸引消费者的注意力。

然而，几个月前，作者的母亲通过直播平台购买了一只品质上乘、价格合理的翡翠手镯，这一经历彻底颠覆了作者对直播产品的固有认知。在此之前，作者一直认为直播平台主要销售的是标准化的工业性商品。这次经历引发了作者对非标准化产品在直播间销售效果的深入思考。于是，与孔德梅老师进行了多次深入的讨论，并最终将研究焦点聚焦于“非标准化产品直播间销售绩效的影响因素分析”这一选题。

通过阅读大量相关研究文献，作者发现以往的研究主要聚焦于主播的粉丝量、互动方式等特征对直播绩效的影响，而对于直播间产品特征这一关键因素的影响则探讨得相对较少。即便在现有的研究中，仅有寥寥几篇文献涉及到了直播间产品特征的话题，但它们也仅仅关注了产品数量和产品平均价格这两个较为表面的因素，对于更深层次的产品特性，如产品的多样性、独特性等方面则缺乏深入的探讨。

然而，在实际直播销售中，选品问题无疑是一个至关重要的环节。不同的产品特性可能会对直播间的观众吸引力、购买转化率以及整体销售业绩产生显著的影响。因此，对于直播间产品特征的深入研究，不仅有助于揭示其对直播绩效的具体影响机制，还能为直播从业者提供更具体、更有针对性的选品策略建议，从而进一步提升直播间的销售业绩和观众满意度。鉴于此，本研究将重点关注直播间产品特征（即产品多样性）对直播绩效的影响，以期填补这一研究领域的空白，并为直播行业的健康发展提供有益的参考。

2. 每一个队员在论文撰写中承担的工作以及贡献

在论文撰写过程中，作者深入阅读并学习了相关文献，聚焦于直播间产品选择问题与直播绩效（即直播间商品交易总额和粉丝增长量）之间的关系。基于抖音直播平台的真实数据，通过计量经济学模型，作者实证分析了直播间产品多样性对直播间商品交易总额和粉丝增长量的具体影响，并进一步探讨了主播特征在这一过程中的调节作用。作为论文的唯一作者，作者独立完成了论文的所有内容，包括文献综述、数据收集、模型构建、数据分析与解释等，同时积极与指导老师沟通协调，不断深化和完善研究内容。

3. 指导老师与学生的关系，在论文写作过程中所起的作用，及指导是否有偿

在前期的研究计划阶段，作者在阅读相关文献时，深受清华大学经济管理学院孔德梅老师已发表研究内容的启发。于是，作者写信与孔老师联系，分享并探讨了学术观点和问题。本文的雏形正是在孔老师的指点下逐渐形成的。当作者表达出希望针对该题目深入研究并参加丘成桐中学科学奖的意愿时，孔老师欣然接受邀请，成为了作者的指导老师。

在论文写作过程中，孔老师不仅推荐和提供了宝贵的学术论文参考，还悉心指导作者细化了计量经济学模型、变量刻画和结果分析。尤为值得一提的是，孔老师的指导是完全无偿的。正是在她耐心指导下，本篇论文才得以顺利完成。

4. 他人协助完成的研究成果

在问题讨论的前期阶段，作者曾接受了孔德梅老师推荐的文献，并基于对这些文献的深入阅读，逐步细化了研究问题。