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Exploring the Interaction Between Streaming Modes and Product Types in E-Commerce Sales

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Abstract: The different combinations of streaming media modes and product types influence the sales performance of streaming e-commerce. However, which combination is more effective in boosting product sales is unclear. Drawing on the cognitive fit theory, we collected sales data from 564 short videos and live streams on TikTok to investigate how the interaction of streaming media mode and product type impacts streaming e-commerce sales quantity. This study reveals that short video e-commerce works better at selling search products. In contrast, live-streaming e-commerce excels at boosting experience products, particularly expensive ones. Furthermore, the interaction effect between streaming e-commerce mode and product type is more significantly affected by low-priced products. This research contributes to understanding streaming e-commerce and offers valuable insights for e-commerce stakeholders.

Keywords: streaming e-commerce; streaming media mode; live streaming e-commerce; short video e-commerce; product type

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1. Introduction

The rise of streaming media paves the way for streaming e-commerce, which leverages live streaming and short video platforms such as TikTok for online shopping [1]. These platforms possess social attributes that foster user interaction. By December 2023, 1.053 billion people use streaming media, making up 96.4% of all Internet users [2]. Consequently, streaming e-commerce represents and provides an innovative and unique e-commerce model that draws on and monetizes this user traffic [3].

Short-video e-commerce (SVE) and live-streaming e-commerce (LSE), the two major modes of streaming e-commerce, have unique features that differentiate them from traditional e-commerce. LSE combines live streams with online shopping, increasing engagement and sales [4]. This integration merges social media with the purchasing process, making the decision-making process social and immediate, such as LSE on TikTok [5]. Conversely, SVE integrates product demonstrations within short video content [6]. This approach combines visual media with products, providing convenient, personalized consumption experiences. Extant studies show that live streaming supports real-time interaction, promoting customer involvement [7]. The adoption of live-streaming strategies leads to a substantial increase in the sales performance of online products [8]. Similarly, SVE affects sales and increases the store's dynamic score, including service quality and customer satisfaction [9].

While streaming e-commerce significantly boosts online shopping, sales performance varies considerably across different streaming modes (e.g., live streaming mode vs. short video mode). Moreover, sales of various products under the same mode show significant variations, which could be attributed to differences in the choice of streaming media modes [10] and product types [11]. Live streaming emphasizes authenticity and has a longer duration, whereas short videos allow for content editing to highlight visual impact and can be replayed and shared repeatedly.

Live streaming and short videos have different presentation forms, offering distinct shopping experiences for consumers when selling various products. Different types of products entail distinct decision-making tasks. The alignment between streaming media modes and products affects consumers' purchasing desires [12]. When the product matches the streaming e-commerce mode, it better fulfills consumers' cognitive needs and enhances the shopping experience. Conversely, suppose there is a mismatch between the streaming e-commerce modes and the products. In that case, consumers may need to expend additional effort to process information, reducing consumer satisfaction and negatively impacting purchasing behavior. Therefore, it is crucial to examine the interplay of streaming e-commerce mode and product type on sales performance [13].

Research on streaming e-commerce primarily focuses on investigating consumer behavior, such as consumers' motives for viewing live streams [14] and factors influencing consumer purchasing [15] and participation behaviors [16]. Another research explores how different combinations of celebrities, content, consumers, and endorsed products affect audience evaluation [12]. The distinct impacts of live streaming and short videos on consumers in the tourism [17] and gaming industries are investigated [18]. Different products have different attributes, and there are differences in consumers' purchasing needs for different types of products. Nonetheless, the interplay of streaming e-commerce mode and product type on sales performance has not been examined empirically.

This paper explores how the interaction between streaming e-commerce modes and product types affects sales performance. The e-commerce section of the TikTok platform offers a wide variety of products with varying prices for the same items. The price of a product is a key factor influencing consumer purchasing decisions, and higher prices potentially reduce sales quantity. Therefore, we examine how various products' prices influence the interaction of streaming e-commerce mode and product type. Considering the alignment between information forms of streaming media modes and consumers' cognitive structures, we adopt the cognitive fit theory to explain why certain streaming e-commerce modes are more suitable for different types of products. The primary research question is how to fit streaming e-commerce modes with product types to enhance sales. We gathered sales data from 282 products sold in 564 live streams and short videos from TikTok to examine the research model. Our findings enrich the theories of the relevant research field and offer valuable guidance for streaming e-commerce stakeholders regarding streaming media strategies.

2. Literature Review

2.1. Live Streaming E-Commerce

LSE is an innovative business strategy and a novel approach that combines e-commerce with live streaming media mode [19]. It involves streamers showcasing and demonstrating products to consumers in real-time [20], encouraging them to take action to purchase [21]. The live interaction feature enhances social activities, allowing hosts and users to communicate in real time and enabling instant trust among consumers [22]. This immersive shopping experience draws a lot of participants, leading to increased consumption [23]. The interface of LSE is depicted in Figure 1.

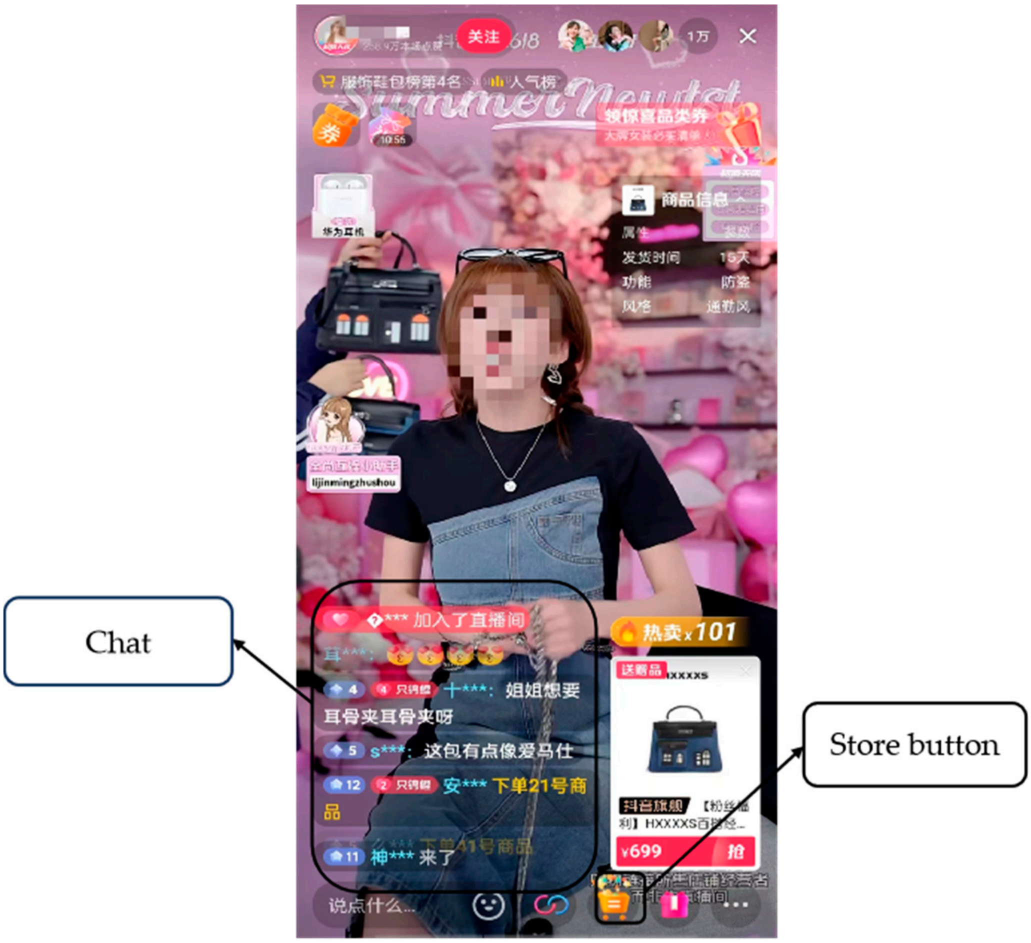

Figure 1. The interface of LSE.

LSE involves various elements, such as streamers, products, consumers, and social interaction. Extant research tries to understand how the alignment between these elements impacts consumers' purchase intentions. For instance, the impact of pairings between internet celebrities, live content, and products on consumer attitudes is investigated [12]. Moreover, Chen et al. [24] found that the fit between live contexts and products can reduce product uncertainty and promote consumer purchases. Additionally, Shang et al. [25] revealed how the appropriateness of live-streaming backgrounds and products affected consumers' purchase intentions. Not all products possess the same attributes; some emphasize objective characteristics, while others focus more on experiential attributes. Although existing research has explored the fitness between live streaming and products, the role of product type within streaming media modes has yet to be thoroughly examined.

2.2. Short Video E-Commerce

SVE involves users creating and sharing videos to advertise products [26]. In these videos, product information is displayed, and users can click the links to the products' homepage [3]. Retailers benefit a lot from the advanced editing and replay features of short videos to showcase their products in a creative way. Thus, they can capture the attention of consumers [6]. While watching the videos, consumers can easily purchase the products by clicking on the "shopping cart" icon located in the video (see Figure 2).

Figure 2. SVE interface.

Current research is dedicated to investigating the impact mechanism of short videos on consumer behavior [27]. Ge et al. [26] explored how SVE's social appeals and vividness affected product sales. Furthermore, the effect of short video attributes on consumer behavior varies by product type. Others also examine how two advertising strategies drive product traffic for TikTok online retailers within the streaming media platform from the seller's perspective [6]. Previous research focuses only on the effect of consumer behavior within one mode. It indicates that both LSE and SVE positively influence online sales. In contrast, our study investigates both LSE and SVE to explore the differences in consumer choices between these two modes of streaming e-commerce.

2.3. Classification of Products

Products can be categorized based on their information characteristics into two types, namely, search products and experience products [28]. Search products are defined as those products whose key attributes (such as performance, specifications, and functionality) can be evaluated and compared based on readily available, objective information before purchase. But for experience products, like perfume and clothes, consumers can only judge the quality characteristics after purchase or use, often involving subjectivity and uncertainty [29]. These product types emphasize the informational features and experiential attributes of the product.

Product type is a considerable factor affecting sales performance in streaming e-commerce. Live streaming is especially effective in convincing consumers to buy experience products [4]. Sales performance varies among streamers when selling different types of products. Yang et al. [30] found male streamers were more successful in selling experience products like skincare and cosmetics, while female streamers outperformed males in selling search products. Furthermore, Xiao et al. [3] observed that for search products, characteristics related to performance expectations in short videos had a greater impact on consumer engagement behavior compared to experience products. Studies have examined the effectiveness of LSE and SVE separately, but there is a lack of discussion on the interaction between streaming e-commerce modes and product types.

2.4. Cognitive Fit Theory

Cognitive fit theory emphasizes how the fit between decision-making tasks and information representation impacts individual problem-solving performance [31]. The effectiveness of problem-solving relies on the information representation and the task's characteristics. LSE and SVE are two distinct forms of representing information, and consumers encounter different decision-making tasks when purchasing various types of products. Consumers can reduce cognitive effort and make decisions more quickly when the information representation aligns with the task. On the other hand, when the information representation does not align with the task, cognitive fit is not achieved. This misalignment requires users to exert additional cognitive effort to adjust their mental representation, ultimately resulting in lower performance compared to situations where cognitive fit is present.

Cognitive fit theory is validated across multiple disciplines, including data visualization and assessment of cognitive effect [32]. Cognitive fit occurs when the components of a problem form a coherent mental representation or when external information aligns with the user's internal representation [33]. Cognitive fit theory offers a valuable theoretical framework for understanding the matching between streaming e-commerce modes and consumers' online shopping tasks.

3. Research Model and Hypotheses

The research model of this study is shown in Figure 3, illustrating how streaming e-commerce mode and product type interact to affect product sales. Furthermore, price moderates the interaction between streaming e-commerce mode and product type.

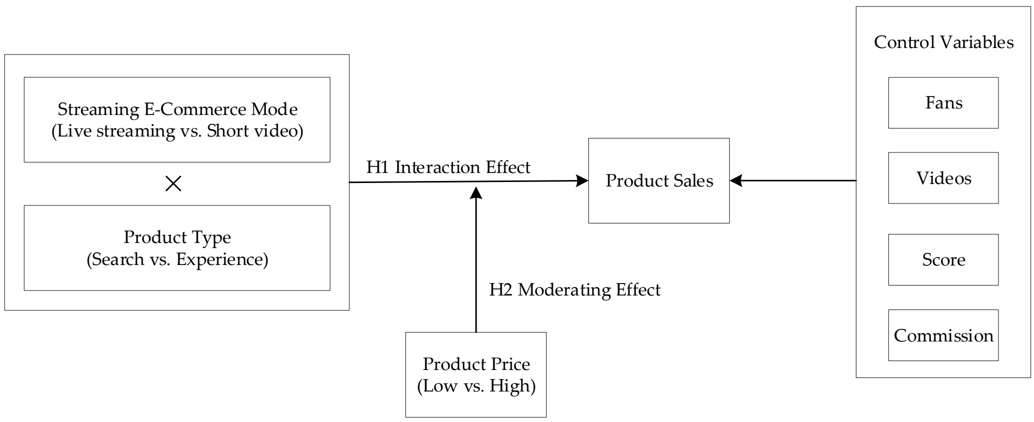

Figure 3. Research model.

3.1. The Interaction Effect of Streaming E-Commerce Mode and Product Type

In streaming e-commerce, the effective presentation of product information is essential for awakening consumers' purchasing intentions. When purchasing various types of products, consumers have distinct product information needs. The presentation of product information in different modes of streaming e-commerce varies. Cognitive fit theory suggests that individuals enhance their decision-making efficiency when the presentation of product information aligns with the cognition process required for the task [31].

In LSE, product information is presented to consumers through live streaming, which features a high degree of interactivity [22]. The product information presentation form of real-time display and interactive better aligns with consumers' cognitive processes for evaluating products that are not easily assessed visually, thereby improving the efficiency of purchasing decisions. Conversely, SVE utilizes pre-recorded videos, offering a stronger visual effect [13]. This product information representation aligns with consumers' cognitive process by quickly obtaining product information, accelerating their purchasing decisions. Search products have clear product attributes: consumers can use SVE quickly, have more comprehensive product information, and experience products rely more on subjective feelings. LSE real-time display and interactive features can help consumers reduce information asymmetry. Product types and streaming e-commerce modes match can help consumers improve the efficiency of purchase to enhance the shopping experience. Thus, we hypothesize the following:

H1. *The interaction effect of streaming e-commerce mode and product type affects the sales of products.*

Search products facilitate effortless searches and enable quality assessments based on accessible information [28]. These products are easily described with objective search attributes, facilitating comparisons. The performance-expected characteristics of short video e-commerce reflect product functionality and usefulness, making it easier for potential consumers to evaluate search products [3]. Short videos can quickly and intuitively display the search attributes of products, better meeting consumers' information needs for search products, reducing their cognitive burden, and encouraging purchase decisions. Live streaming usually has a longer duration than short videos, requiring consumers to wait for the streamer to explain and display the product, necessitating additional cognitive efforts [17]. This increases consumers' cognitive load and negatively affects their shopping experience. Hence, the SVE mode is more effective than LSE in satisfying consumers' information needs during the purchase decision-making process for search products. Thus, we hypothesize the following:

H1a. *SVE is more appropriate for search products than LSE in streaming e-commerce.*

Consumers' needs for product information vary according to the type of the products. In terms of experience products, live interactive presentations have a greater impact than search products. It takes more time for consumers to understand the attributes of experience products, leading to higher search costs compared to search products [28]. Consumers also face more uncertainty when evaluating the quality of experience products [24]. This requires more cognitive effort along with subjective perceptions and greater perceived risks [34]. Live streamers help reduce product uncertainty through alternative product trials and interactive sharing [20]. Live streaming enhances real-time interaction and authentic experiences, reducing cognitive tasks for experience products and positively influencing consumers' purchase intentions. SVE focuses on displaying product highlights, but they are less effective at presenting detailed features and attributes. This may affect consumers' in-depth understanding and perception of product experience attributes, requiring greater cognitive effort and influencing purchasing decisions. Live streaming is more effective than short videos in meeting consumers' experience needs during the decision-making process for experience products. Therefore, we hypothesize the following:

H1b. *LSE is more effective than SVE in promoting experience products in streaming e-commerce.*

3.2. Moderating Effect of Product Price

Product prices significantly influence consumer purchasing decisions [35]. For low-priced items, consumers may not require extensive information processing and evaluation. Short videos typically last under 3 min and highlight key points. This can effectively fulfill consumer needs for quickly obtaining information and expediting purchase decisions for search products. Higher-priced products often carry greater perceived risks. Price sensitivity is closely linked to consumer purchasing decisions, even in the presence of positive factors such as product quality and trust [36]. Consumers exert more cognitive effort to assess the value of high-priced products.

The live interaction of LSE furnishes customers with rich and useful product information to assist them in making purchase decisions [7]. The higher the consumer satisfaction, the less sensitive they are to price [37]. SVE meets consumers' information needs for low-priced products, saving them time costs and improving decision-making efficiency. In contrast, LSE reduces consumer uncertainty risks and aids decision-making for high-priced products. Short video e-commerce meets consumers' information needs for low-priced products, saving them time and improving decision-making efficiency. Thus, we hypothesize the following:

H2. *Product price negatively moderates the impact of the interaction effect between streaming e-commerce mode and product type on sales.*

4. Methodology

4.1. Data Collection

We adopted TikTok as the research sample source. It is a well-known short video social platform with a large user base, with monthly active users reaching 1.58 billion [38]. TikTok provides SVE and LSE, covering a wide range of product categories. The sample selection period is from 21 June 2023 to 28 August 2023. In our study, the sample consists of clothing, digital home appliances, beauty, daily necessities, and food. Digital home appliances and daily necessities (such as smartphones, cameras, and teacups) typically have standardized technical specifications (e.g., size, performance, brand) that allow consumers to assess and evaluate them based on product descriptions [10]. In contrast, products like cosmetics, clothing, and food are highly reliant on sensory attributes, and consumers cannot evaluate their quality through objective information alone. Instead, consumers must rely on actual use or experience to make an informed judgment. Digital home appliances and daily necessities represent search products, while cosmetics, clothing, and food represent experience products. We selected those sample products that adopted both short video and live streaming modes for promotion. To ensure data quality, live streaming and short videos released at least 30 days before the data collection date were chosen. For the data collection, a total of 282 distinct products were selected from TikTok, with 104 search products and 178 experience products, each corresponding to data collected from both live streaming and short video modes. This resulted in a total of 564 pieces of product information, with each product represented once in both modes. Data items included product names, product prices, number of short videos or live streaming associated with the product, product sales quantity, product ratings, product commissions, and streamer's fan counts. Product classification is detailed in Table 1.

4.2. Variable Measurement

The dependent variable, sales data, is quantified by aggregating the total daily sales quantities resulting from live streaming and short video promotions of the products.

Table 1. Product categories are categorized as search or experience.

Product Type	Category	Number	Examples
Search products	Digital products	48	Vacuum cleaner, earphones
	Daily necessities	56	Wipes, teacups
Experience products	Cosmetics	60	Perfume, rouge
	Food	47	Juice, cakes
	Clothing	71	Trousers, dresses

The independent variables are the types of products and the modes of streaming e-commerce. We encoded the variable of product type. Experience products are marked as 0, and search products are marked as 1. For the streaming e-commerce modes, we categorized them as live streaming (marked as 0) and short video (marked as 1).

The moderating variable in this study is product price, which is defined based on whether the price is above or below the median price for similar products. If a product's price is at or below the median, it is considered low-priced and given a value of 0. Conversely, if the price is above the median, it is considered high-priced and given a value of 1.

The control variables are the number of fans streamers possess, the quantity of product-related videos, product ratings, and product commissions. The number of fans can reflect the seller's influence on TikTok, and it can better illustrate the seller's experience compared to the duration. Product ratings can reflect consumer satisfaction with the product, and the number of associated videos can reflect the product's popularity. The commission rate can measure the sales revenue of a product. The number of fans is measured by the aggregated count of followers for streamers who engaged in live streaming or short video sales activities within the 30 days preceding the data collection date. The short video count is measured by the cumulative number of live streaming or short videos showcasing products on the TikTok e-commerce platform within a month. The variable of product rating is measured by the consumer review scores for the product. The product commission is measured by the percentage fee charged by the platform to the seller for each sale. The above factors are shown to affect online sales in streaming e-commerce [39,40]. The variables are described in Table 2.

Table 2. The description of variables.

Variables		Description
Dependent variables	*Sales*	Total product sales quantity within a month
Independent variables	*ProdType*	*ProdType* = 1 if the product is a search product; otherwise, *ProdType* = 0
	ModeType	0 = live streaming; 1 = short video
Moderating	*Price*	*Price* = 1 if the product is high priced; otherwise, *Price* = 0
Control	*Fans*	The total fans
	Videos	The aggregate count of live streams or short videos associated with the product
	Score	Rating of the product
	Commission	The commission rate for the product

4.3. Descriptive Statistical Analysis

The descriptive statistical analysis of the variables is displayed in Table 3. It reveals that the mean and standard deviation of the *Sales*, *Fans*, and *Videos* variables have wide variations, indicating significant differences in the sample. The distribution of the other variables in the sample is relatively centralized, with no significant dispersion. Due to the substantial differences in the mean and extreme values of product sales quantity, fan counts, and the number of videos compared to the dependent variable data, this study applies natural logarithm transformations to these three variables to improve the robustness of the results. The correlation coefficients between the variables are given in Table 4.

Table 3. Descriptive statistical analysis of variables.

Variables	Observations	Mean	SD	Min	Max
Sales	564	2671	9920	10	100,000
ProdType	564	0.369	0.483	0	1
ModeType	564	0.500	0.500	0	1
Fans	564	3,188,915	10,392,006.095	4233	112,019,170
Videos	564	383.300	842.400	10	6520
Score	564	4.816	0.118	4.210	5
Commission	564	0.272	0.125	0.010	1.250

Table 4. Correlation Coefficients.

Variables	*Sales*	*ProdType*	*ModeType*	*Fans*	*Videos*	*Score*	*Commission*
Sales	1						
ProdType	−0.001	1					
ModeType	0.041	0	1				
Fans	0.451 ***	0.112 ***	0.080 *	1			
Videos	0.608 ***	0.042	−0.044	0.614 ***	1		
Score	0.0178	−0.096 **	0	−0.062	0.031	1	
Commission	0.138 ***	−0.116 ***	0.014	0.160 ***	0.269 ***	−0.030	1

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The same as below.

4.4. Regression Analysis

The following multiple linear regression models were constructed:

$$\begin{aligned} LnSales = \; & \beta_0 + \beta_1 ProdType + \beta_2 ModeType + \beta_3 ProdType \times ModeType \\ & + \beta_4 LnFans + \beta_5 LnVideos + \beta_6 Score + \beta_7 Commission + \varepsilon \end{aligned} \tag{1}$$

$$\begin{aligned} LnSales = \; & \beta_0 + \beta_1 ProdType + \beta_2 ModeType + \beta_3 Price + \beta_4 ProdType \times ModeType \\ & + \beta_5 ProdType \times ModeType \times Price + \beta_6 LnFans + \beta_7 LnVideos + \beta_8 Score \\ & + \beta_9 Commission + \varepsilon \end{aligned} \tag{2}$$

In Equations (1) and (2), *Sales* denotes the product sales quantity, and *ProdType* indicates the product type, where e-commerce products on the TikTok platform are categorized as experience products and search products (experience products = 0, search products = 1). *ModeType* denotes the streaming e-commerce modes (live streaming = 0, short videos = 1). *LnFans*, *LnVideos*, *Score*, and *Commission* are controls; ε is the random error term.

5. Results

The results of the multiple linear regression analysis are depicted in Table 5. As shown in Model 1 of Table 5, *LnFans*, *LnVideos*, and *Score* have positive effects on *LnSales* separately (β_4 = 0.080, $p > 0.1$; β_5 = 0.833, $p < 0.01$; β_6 = 0.480, $p > 0.1$). *Commission* is negatively correlated with *LnSales* ($\beta_7 = -1.984$, $p < 0.01$). The interaction of streaming e-commerce mode and product type significantly enhances product sales quantity (Model 3, β = 1.389, $p < 0.01$), confirming hypothesis H1. *ModeType* influences *LnSales*, indicating the main effect of SVE is significant (Model 2, β = 0.596, $p < 0.01$). In Model 3, there is a negative correlation between *ProdType* and *LnSales* ($\beta = -0.877$, $p < 0.01$), while *ModeType* has no significant effect on *LnSales* (β = 0.063, $p > 0.1$). This indicates that for search products, choosing SVE enhances product sales quantity, supporting hypothesis H1a. There is no significant difference in the main effect of product type on sales quantity in Model 2

($\beta = -0.191$, $p > 0.1$), while it has a significant effect in Model 3 ($\beta = -0.877$, $p < 0.01$). This indicates that for experienced products, choosing LSE increases product sales, confirming hypothesis H1b. In Model 4, the coefficient of the product price variable ($\beta = 0.421$, $p < 0.01$), the second-order interaction term between product type and streaming e-commerce mode ($\beta = 1.708$, $p < 0.01$), and the third-order interaction term between product price, product type, and streaming e-commerce mode ($\beta = -1.563$, $p < 0.01$) are all significant. This indicates that the product price negatively moderates the impact of the interaction between streaming e-commerce mode and product type on sales quantity, supporting hypothesis H2. The results of the hypothesis are shown in Table 6.

Table 5. Multivariate linear regression result.

	(1)	**(2)**	**(3)**	**(4)**
LnFans	0.080	0.095 *	0.083	0.104 **
	(0.052)	(0.052)	(0.051)	(0.049)
LnVideos	0.833 ***	0.883 ***	0.869 ***	0.845 ***
	(0.066)	(0.066)	(0.065)	(0.063)
Score	0.480	0.338	0.366	0.419
	(0.625)	(0.621)	(0.609)	(0.589)
Commission	−1.984 ***	−2.341 ***	−2.290 ***	−2.158 ***
	(0.617)	(0.619)	(0.608)	(0.589)
ProdType		−0.191	−0.877 ***	−1.038 ***
		(0.153)	(0.210)	(0.265)
ModeType		0.596 ***	0.063	0.701 ***
		(0.151)	(0.187)	(0.251)
ProdType × *ModeType*			1.389 ***	1.708 ***
			(0.297)	(0.377)
Price				0.421 ***
				(0.160)
ProdType × *ModeType* × *Price*				−1.563 ***
				(0.374)
_cons	−1.263	−1.140	−0.795	−1.638
	(3.039)	(3.022)	(2.967)	(2.883)
N	564	564	564	564
R-sq	0.372	0.390	0.413	0.432

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

Table 6. Hypothesis test results.

Hypothesis	**Coefficient**	**Significance**	**Result**
H1	1.389	***	Supported
H1a	0.596, 0.063	***	Supported
H1b	−0.191, −0.877	***	Supported
H2	−1.563	***	Supported

Note: *** $p < 0.01$.

The findings of regression analysis do not specify the optimal streaming e-commerce mode for diverse product types across different price ranges. To address this, we conducted separate regression analyses for high and low-priced products. Fisher's permutation test was employed to evaluate the significance of coefficient differences between the two product groups following separate regression analyses. A p-value below 0.1 indicates a statistically significant disparity in variable impact on sales between the two product groups.

The results from Table 7 for Model 2 indicate that the modes of streaming e-commerce are influenced by variations in product prices. No statistically significant difference exists in how product type influences sales between low-priced and high-priced categories. The results show that using SVE enhances sales for low-priced products while choosing LSE boosts sales for high-priced products (β_{low} = 1.498, $p < 0.01$; β_{high} = −0.567, $p < 0.01$). The findings from Model 3 indicate significant differences in the interaction coefficient between the types of products and the modes of streaming e-commerce between groups (β = 1.668, $p < 0.01$ in the low-priced group). Conversely, for the higher-priced group, the interaction coefficient of product type and streaming e-commerce mode is not statistically significant (β = 0.365, $p > 0.1$). This suggests that the interaction effect of product type and streaming e-commerce mode does not significantly impact sales of high-priced products.

Table 7. Group regression results.

Variables	**(1)**			**(2)**			**(3)**		
	Low Price	**High Price**	***p* Value**	**Low Price**	**High Price**	***p* Value**	**Low Price**	**High Price**	***p* Value**
LnFans	0.065 (0.079)	0.109 (0.068)	0.329	0.140 * (0.074)	0.107 (0.068)	0.339	0.107 (0.072)	0.106 (0.068)	0.482
LnVideos	0.850 *** (0.095)	0.823 *** (0.092)	0.426	0.903 *** (0.088)	0.748 *** (0.096)	0.133	0.894 *** (0.085)	0.746 *** (0.096)	0.121
Score	−0.311 (0.907)	1.520 * (0.860)	0.062	−0.453 (0.841)	1.635 * (0.859)	0.038	−0.440 (0.817)	1.636 * (0.859)	0.032
Commission	−2.221 ** (0.895)	−1.520 * (0.852)	0.311	−2.882 *** (0.829)	−1.294 (0.877)	0.132	−2.668 *** (0.807)	−1.320 (0.878)	0.168
ProdType				−0.240 (0.199)	−0.046 (0.228)	0.255	−1.057 *** (0.269)	−0.229 (0.318)	0.048
ModeType				1.498 *** (0.199)	−0.567 *** (0.216)	0.000	0.754 *** (0.258)	−0.680 *** (0.255)	0.000
ProdType × *ModeType*							1.668 *** (0.383)	0.365 (0.440)	0.019
_cons	2.676 (4.427)	−6.639 (4.186)		1.605 (4.112)	−6.603 (4.188)		2.343 (3.999)	−6.519 (4.191)	
N	310	254		310	254		310	254	
R-sq	0.363	0.381		0.465	0.398		0.497	0.400	

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

The dependent variable was log-transformed and subjected to linear regression analysis. Considering that the dependent variable, product sales, consists of non-negative integer data and may exhibit overdispersion, this study employed a negative binomial regression model to re-examine the research hypotheses, thereby demonstrating the robustness of the findings. The results of the robustness test are shown in Table 8. All results are consistent with those of the main analyses described above.

Table 8. Robustness check results.

	(1)	**(2)**	**(3)**
LnFans	0.016 (0.013)	0.014 (0.013)	0.017 (0.013)
LnVideos	0.153 *** (0.016)	0.151 *** (0.016)	0.146 *** (0.016)
Score	0.092 (0.157)	0.094 (0.157)	0.107 (0.157)
Commission	−0.456 *** (0.158)	−0.445 *** (0.157)	−0.426 *** (0.159)
ProdType	−0.034 (0.038)	−0.162 *** (0.054)	−0.206 *** (0.073)
ModeType	0.089 ** (0.037)	−0.008 (0.047)	0.104 (0.064)
ProdType × *ModeType*		0.256 *** (0.075)	0.310 *** (0.098)
Price			0.133 ** (0.062)

Table 8. *Cont.*

	(1)	(2)	(3)
ProdType × ModeType × Price			−0.318 ***
			(0.108)
_cons	0.394	0.467	0.314
	(0.767)	(0.767)	(0.772)
N	564	564	564

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

6. Discussions

6.1. Discussion of the Findings

This research examines the interaction effect of streaming e-commerce modes and product types on sales, as well as the influence of prices on this interaction effect. We use sales data from the TikTok platform to validate the research model. The results show that matching the suitable streaming e-commerce mode with the product type significantly improves sales performance. The study finds that LSE performs better than SVE in selling experience products. This supports previous findings that live streaming is more effective in convincing online users to purchase experience products [41]. When purchasing experience products, consumers rely on personal preferences and subjective feelings, requiring more detailed information to evaluate the product's experiential attributes. Live streaming provides consumers with an immersive experience, allowing them to intuitively understand experience products more effectively than short videos.

The results indicate that SVE is more effective than LSE in increasing sales for search products, suggesting that consumers value product quality information when purchasing search products. SVE displays the key features of a product in a short amount of time, offering significant convenience [17]. The presentation form of short videos is more fitted with consumers' decision-making process when buying search products, and it also lowers consumers' search costs. These findings explain how different streaming e-commerce modes match various product types, which provides valuable insights into the matching mechanism.

In addition, the product price influences the interaction of streaming e-commerce mode and product type on product sales. Specifically, for low-priced products, this relationship remained valid. However, for higher-priced products, the interaction effect disappears. High-priced products typically involve greater perceived risk and higher price sensitivity. Consumers may need to exert more cognitive effort and rely on more reliable information sources, such as brand reputation, reviews, and expert opinions, rather than solely relying on the appeal and engagement provided by live streaming or short videos.

6.2. Theoretical Implications

This study contributes to the existing literature on streaming e-commerce by confirming the interaction between streaming e-commerce mode and product type on sales. Previous research mainly explores how the attributes of streaming e-commerce impact consumer behavior [42,43]. However, the impact of the modes of streaming e-commerce on sales has not been explored. Hence, this study offers a new insight into the modes of streaming e-commerce.

Second, based on cognitive fit theory, we examine how streaming e-commerce modes and product types affect sales. Regarding search products, it's easy to describe them by their attributes. For experiential products, it is more challenging to obtain information through search compared to directly experiencing or visualizing the product itself [29]. Real-time interactive scenarios are more convincing for consumers when purchasing products [44]. This aligns with how consumers decide to purchase experience products and encourages their buying behavior. SVE fits well with how consumers decide to buy search products, reducing the time spent searching for desired products and meeting consumers' information needs during the decision-making process for purchasing search products. Therefore, this study provides a theoretical foundation for exploring streaming e-commerce.

Third, we examine how product prices affect the different combinations of streaming e-commerce modes and product types on product sales. The research indicates that lower product prices make SVE more effective in encouraging consumers to buy search products. LSE is more suitable for promoting purchases of experience products. However, this matching effect becomes weaker as product prices go up. Thus, our study emphasizes the important role of product price in streaming e-commerce.

6.3. Practical Implications

The findings offer insights to help companies develop effective streaming e-commerce strategies. For search products, SVE should highlight product information to facilitate consumer decision-making and provide clearer product descriptions, such as price, performance, and quality. Conversely, for experience products, LSE should focus on displaying the product's use and experiential effects. Streamers build trust through interaction and can share personal experiences to enhance the perceived value of the product.

Furthermore, e-commerce stakeholders should tailor their strategies based on product prices, using live streaming for high-priced products and short videos for low-priced products. Enterprises should utilize short videos to emphasize the cost-effectiveness of their products and attract consumers. Additionally, e-commerce stakeholders should develop high-quality live-streaming content to enhance consumers' perception of the value of high-priced items. This approach can reduce operating costs and increase sales.

Finally, the research findings contribute to optimizing the design and functionality of e-commerce platforms. Streaming e-commerce platform operators should ensure that the interface design meets the shopping needs of consumers. For search products, the focus should be on providing comprehensive product information and enhancing search convenience. For experience products, interface design should prioritize enhancing visual appeal and user experience to meet consumer preferences and needs. This will reduce operating costs and boost sales.

6.4. Limitations and Future Research

This paper explores how the combined influence of streaming e-commerce and product type affects sales. Product classifications may extend beyond this classification method, with products often having multiple attributes at the same time. Future research could explore more nuanced classifications of products. This would examine how different product attributes interact with various streaming e-commerce modes. Second, we only explore the moderating impact of the product price on the interaction effect of streaming e-commerce mode and product type. Other factors, such as brand familiarity and the language characteristics of streamers, may also impact product sales. These can be further studied in the future.

7. Conclusions

Drawing on cognitive fit theory, this study examined how different combinations of streaming e-commerce and product type influence sales performance. Through an analysis of sales data on TikTok, the study reveals that the interactive effect of streaming e-commerce mode and the product type influences sales greatly. Specifically, SVE outperforms LSE in increasing sales of search products, while experience products are more effectively marketed through LSE. Moreover, we find that the price of products moderates the impact of the interaction effect between streaming e-commerce mode and product type on product sales. The findings expand the theoretical understanding of matching streaming e-commerce modes with product types and offer strategic guidance for e-commerce stakeholders.

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