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Factors Affecting Sales of Import E-Commerce Live Streaming in Cross-Border Trade

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Abstract: *E-commerce live streaming has garnered widespread social attention as a new marketing and social interaction method. Compared with traditional e-commerce models, e-commerce live streaming offers stronger interactivity and an immersive shopping experience for consumers. Drawing on the Kotler model and theoretical analysis, this study identifies four dimensions by which social attention impacts the sales volume of imported e-commerce live streaming. Subsequently, based on theoretical hypotheses and research models, this paper empirically quantifies the impact of communicativeness, identifiability, interactivity, and followability on the sales volume of imported e-commerce live streaming. The study employs mixed panel regression analysis, fixed-effects regression analysis, and random-effects regression analysis to select the most appropriate model. To minimize endogeneity, the panel fixed-effects model is ultimately chosen. The research findings indicate that communicativeness does not significantly affect the sales volume of imported e-commerce live streaming, while identifiability, interactivity, and followability have significant positive effects. Among them, interactivity has the most significant impact on sales volume, and followability has the strongest positive effect. Finally, the research results are summarized, and relevant suggestions are proposed for live streaming merchants and hosts, including precise marketing, enriching content, ensuring information transparency, and leveraging opinion leaders.*

Keywords: *Live streaming; Sales; Interactivity; Social attention*

1. Introduction

The 20th National Congress of the Communist Party of China proposed to accelerate the construction of a strong trading nation. Cross-border trade is an important part of China's opening up to the outside world, and cross-border e-commerce (CBEC) has become an important means of promoting international trade (MOU et al., 2020)[1]. China's cross-border e-commerce market has great potential for development. Data from the Ministry of Commerce show that in 2022, China's cross-border e-commerce imports and exports reached 2.11 trillion yuan, a year-on-year increase of 9.8%, with imports accounting for 26% of the total cross-border e-commerce trade volume, indicating significant room for growth.

Live streaming e-commerce has emerged as a new means of promoting cross-border trade. As of June 2022, the number of e-commerce live streaming users in China approached 470 million. In 2021, the transaction scale of China's e-commerce live streaming market reached 2361.51 billion yuan. Moreover, as of March 2022, the cumulative number of views on Taobao Live, the largest consumer live streaming platform in China, had exceeded 50 billion, witnessing the synchronous growth of social attention and transaction volume in e-commerce live streaming. The domestic e-commerce live streaming model first appeared around March 2016, when Alibaba initiated a trial of live streaming on the Taobao e-commerce platform to prolong consumers' browsing and purchasing time. Over time, the e-commerce live streaming model has demonstrated remarkable marketing capabilities. E-commerce platforms such as Suning, Amazon, and *Temu* have attempted to expand their live streaming businesses, and social media platforms like *Kuaishou*, *Tiktok*, *Readnote*, and Tencent have also vigorously developed live streaming sales models.

The development of imported e-commerce live streaming has been rapid. Due to its high consumer participation and good dissemination effects, it has become an important supplement to traditional e-commerce. Imported e-commerce live streaming refers to the business model in which hosts conduct cross-border trade of goods or services through real-time video live streaming. Hosts can display, discuss, and respond to audience inquiries in real time (YANG & LEE, 2023)[2]. Compared with traditional cross-border e-commerce sales models, the "e-commerce + live streaming" model provides consumers with a rich immersive shopping experience and interactive opportunities between hosts and consumers, and has stronger social attributes.

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2. Theoretical Hypotheses

The purchasing intentions of e-commerce live streaming consumers may be influenced by many other factors, such as product descriptions, influencer information sources, content fit, and information transparency. Mou et al. (2020) [1] empirically demonstrated that high-quality product descriptions can enhance consumers' cognitive and situational involvement in cross-border e-commerce transactions but do not significantly affect their purchasing intentions. Liu et al. (2020)[3] found that the professionalism, credibility, and interactivity of hosts have a positive impact on consumers' purchasing intentions. Park et al. (2020)[4], based on the matching hypothesis, discovered that the content fit and source credibility of products endorsed by online celebrities in live streaming increase consumers' purchasing intentions. Xu (2022)[5] defined the accessibility of live streaming as the capacity it provides. His research results indicate that although live streaming does not directly affect consumers' cross-border purchasing intentions, it can enhance them by increasing the transparency of live streaming information.

User identifiability refers to the degree of attitude identification that consumers have towards the live streaming content and hosts during the process of watching e-commerce live streaming. In Kotler's 5A model, the attraction stage is the next stage after the awareness stage. The information source of user identifiability is manifested as users' attraction and approval of the live streaming content, which can be measured by the number of approvals for a single live streaming session.

User interactivity refers to the behavior of consumers sharing their personal evaluation information in the live streaming process to achieve interactive communication between hosts and users. Interactivity can also be interpreted as consumers' inquiries about product information. The information source of user interactivity is manifested as users' responses to hosts and sharing of individual information in the live streaming. Therefore, this paper uses the number of comments in a single live streaming session to measure user interactivity.

In the purchasing transaction relationship of imported e-commerce live streaming, the secondary dissemination of information is based on hosts as opinion leaders, and consumers' support behavior reflects the attention of fan groups. The influence of opinion leaders can be explained together with the quasi-social relationship theory under the mechanism of celebrity endorsement in the 5A model of e-commerce live streaming consumer behavior. In the environment of live streaming social media, the original secondary dissemination model of "media - opinion leader - public" has been broken, and the public is not only a consumer of information but also a producer of information, while the role of opinion leaders as intermediaries in information dissemination is becoming blurred. The information source of followership between hosts and users is manifested as users' long-term attention and following of hosts. Therefore, this paper uses the number of new fans in a single live streaming session to measure followership.

Therefore, this paper proposes the following hypothesis:

H1: The communicativeness of hosts has a significant positive impact on the sales volume of imported live e-commerce, that is, within the statistical period of the research data, the higher the number of daily live streaming page views, the higher the product sales volume on that day.

H2: User identifiability has a significant positive impact on the sales volume of imported live e-commerce, that is, within the statistical period of the research data, the higher the number of daily user approvals, the higher the product sales volume on that day.

H3: User interactivity has a significant positive impact on the sales volume of imported live e-commerce, that is, within the statistical period of the research data, the higher the number of daily user comments, the higher the product sales volume on that day.

H4: The followership between users and hosts has a significant positive impact on the sales volume of imported live e-commerce, that is, within the statistical period of the research data, the higher the number of daily new fans, the higher the product sales volume on that day.

3. Model and Estimation

This section constructs a regression model that includes social attention, product information, and live streaming characteristics to study the impact of social attention and other control variables on the sales volume of imported e-commerce live streaming.

Based on the theoretical analysis and findings of previous studies on other factors affecting live streaming sales, this paper initially constructs a model, which includes four indicators of social attention: communicativeness, identifiability, interactivity, and followership, as well as live streaming product information characteristics and live streaming host characteristics.

To test the impact of social attention on the sales volume of imported live e-commerce, based on the research model, the following econometric model is constructed for regression analysis:

$$Sales_{it} = C + \alpha SA_{it} + \beta Control_{it} + \mu_{it} \tag{1}$$

3.1. Data and settings

In the academic field, the data sources for live streaming research are mainly divided into primary data from questionnaires and secondary data from third-party data platforms. Although collecting data through questionnaires can provide researchers with the most direct and structured information, the design and answers of questionnaires are often subjective, and researchers cannot fully ensure the quality of the answers, thereby affecting the reliability and validity of the research. Therefore, this paper selects secondary data from the third-party data platform, Gray Dolphin Data, for empirical analysis. This paper selects the data of the top 75 bloggers in the global import section of the Gray Dolphin Data platform, and collects and organizes a total of 32,797 panel data entries over 578 days from April 12, 2020, to November 11, 2021, through machine crawling. The panel data collected in this study include live streaming transaction information: the sales volume and sales revenue of this live streaming session; social attention information: the number of live streaming page views, the number of viewers' approvals, the number of user comments, and the number of new fans in the live streaming; product information: product categories, unit price, number of live streaming products, and the number of live streaming sessions on that day; live streaming characteristic information: host appearance score, host distance, host tone, and the geographical location of the live streaming account, etc.

The Pearson correlation coefficient is the quotient of the covariance between two variables and their standard deviations, which can be used to measure the degree of correlation between two variables. The author first tested the linear relationship between variables and the normal distribution, and found that there is a linear relationship between the explanatory variables and the explained variables, and the explanatory variables are normally distributed.

To ensure the authenticity and validity of the data, this paper first conducted a Pearson correlation analysis on the explained variables, explanatory variables, and control variables. The results of the correlation analysis show that the correlation coefficients between each variable are below 0.8, which meets the requirement for the correlation between explanatory variables. To avoid multicollinearity among variables, this paper further conducted a collinearity diagnosis of the variables, and the results showed that the variance inflation factors (VIF) of the variables were all less than 3, indicating no multicollinearity among explanatory variables.

3.2. Regression

Based on the research model, the formula (1) can be expanded as follows:

$$\begin{aligned} Sales_{it} = {} & C + \alpha_1 \mathrm{clicks_{it}} + \alpha_2 \mathrm{likes_{it}} + \alpha_3 \mathrm{reviews_{it}} + \alpha_4 \mathrm{followers_{it}} + \beta_1 \mathrm{times_{it}} + \beta_2 \mathrm{amount_{it}} + \\ & \beta_3 \mathrm{PCT}_{it} + \beta_4 \mathrm{holiday_{it}} + \beta_5 \mathrm{looks_{it}} + \beta_6 \mathrm{distance_{it}} + \beta_7 \mathrm{pitch_{it}} + \mu_{it} + \sigma_i + \gamma_t \end{aligned} \tag{2}$$

Panel data mitigates the endogeneity problem caused by omitted variables, but compared with cross-sectional data, panel data has the problem of heteroscedasticity. Therefore, using mixed OLS regression may not be able to well explain the relationship between the dependent and independent variables. To solve the heteroscedasticity problem of panel data, this paper uses the fixed-effects model to analyze the impact of the four explanatory variables under social attention on the sales volume of imported e-commerce live streaming. The reasons for using the fixed-effects model instead of the random-effects model are twofold. First, the content produced by different live streaming accounts and the same live streaming account over a continuous period of time has a certain similarity, so the assumptions of individual fixed effects and time fixed effects should not be rejected. Second, the fixed-effects model is more robust than the random-effects model, and the fixed-effects model should be chosen when the Hausman test is passed. Moreover, as shown in the following Table 1, there is no significant difference in the estimated coefficients between the fixed-effects model and the random-effects model. Therefore, the fixed-effects model should be used for regression analysis.

The advantage of using the panel fixed-effects model is that if the unobserved residuals are related to the fixed effects, the unobserved factors are differenced when the fixed effects are demeaned. In this case, the fixed effects can reduce the endogeneity problem that may arise because the unobserved factors may be correlated with the explanatory variables.

Referring to Wooldridge's model testing method and the Hausman test results for the random effects model, three models are tested. It is found that when the p-value is less than 0.05, the fixed effects model should be chosen. When the significance level is α=0.05, the equation is significant. The regression results of the fixed effects model show that when identifiability, interactivity, and followership increase, the sales volume of imported e-commerce live streaming will rise, which is consistent with the assumptions H2, H3, and H4 in this paper.

3.3. Empirical Results

The benchmark regression results and the fixed panel regression results verify the previous assumptions H2, H3, and H4, that is, the identifiability, interactivity, and followership of imported e-commerce live streaming have a positive and significant impact on live streaming sales volume. Although the benchmark regression results support the assumption H1, that is, the communicativeness of imported e-commerce live streaming has a positive and significant impact on live streaming sales volume, considering that the fixed panel regression results are more robust and credible, the latter should be adopted. At the same time, although the communicativeness variable is not significant in statistics, its positive coefficient still has some meaning and cannot therefore reject the H1 assumption that communicativeness has a positive impact on the sales volume of imported e-commerce live streaming. Another reason for not completely rejecting the H1 assumption is that the fixed panel regression model has not performed stepwise control variable regression, so it cannot explain the possible moderating effect of control variables on the explanatory variables that leads to the insignificant coefficient of communicativeness.

Table 1: Fixed Effects Panel Regression

Variables	Pooled Panel Regression	Fixed Effects Regression	*Random Effects Regression*
Communicativeness	-0.016***	0.002	0.001
	(0.003)	(0.004)	(0.004)
Identifiability	-0.001	0.006***	0.006***
	(0.003)	(0.001)	(0.001)
Interactivity	0.874***	0.431***	0.442***
	(0.092)	(0.054)	(0.054)
Followability	7.907***	8.046***	8.021***
	(2.973)	(1.123)	(1.122)
Intercept	60966.589***	-2308.055***	78175.884**
	(6455.777)	(410.777)	(39022.807)
Control for Fixed Effects	N	Y	N
N	32797.000	32797.000	32797.000
R2	0.027	0.012	

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

4. Regional Heterogeneity

In addition to consumer purchase information, social attention information, product information, and live streaming characteristics, regional information related to import destinations and production locations is also worth exploring. After analyzing the geographical information of the sample data, it was found that the distribution of IP addresses recorded by different live streaming accounts varies. IP addresses can reveal the actual locations where the live streaming takes place. The author believes that domestic import e-commerce live streaming addresses are import destinations, while foreign import e-commerce live streaming addresses are import production locations.

The clustered distribution of live streaming geographical coordinates can be described in the following Figure 1. The radius of the cluster circle represents the total number of live streams in the same region. The more cluster import live streams within a region during the statistical period, the larger the

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radius of the cluster circle. The color temperature of the cluster circle indicates the live streaming sales situation in that geographical area, with cool colors representing lower sales volumes and warm colors representing relatively higher sales volumes. In other words, a larger-radius warm-colored cluster indicates that there are more live streaming clusters in that geographical location with relatively higher sales volumes. It should be noted that in the figure below, the destinations of overseas import production locations are all China.

Figure 1: Geographical Distribution of Live Streaming.

The geographical distribution of live streaming not only shows that the import production locations of e-commerce live streaming are mostly concentrated in East Asia, Southeast Asia, Australia, and North America, but also indicates that imported products from these regions have a relative advantage and are more likely to gain consumer preferences. At the same time, the geographical distribution reveals the import destination distribution at the provincial level, with these import destinations mainly participating in the import e-commerce live streaming sales process as import distribution locations.

Table 2: Regional Heterogeneity.

Variables	(1)	(2)	(3)	(4)	(5)
	RECP	CEPA	United States	Canada	Europe
Communicativeness	0.003***	-0.068	0.077***	0.001	-0.000
	(0.001)	(0.092)	(0.016)	(0.002)	(0.000)
Identifiability	0.000	0.008	-0.022***	0.003	-0.000
	(0.000)	(0.115)	(0.005)	(0.002)	(0.000)
Interactivity	0.148***	1.073***	2.916***	0.059***	0.006***
	(0.017)	(0.407)	(0.154)	(0.014)	(0.001)
Followability	1.128***	-32.446	-7.197	1.861***	0.003
	(0.377)	(20.588)	(6.617)	(0.533)	(0.008)
Times	-416.255***	-5434.725	-915.677	-4.710	-0.499
	(130.988)	(5493.718)	(846.824)	(50.510)	(3.124)
Goods Number	8.742***	27.262	10.327	-1.092	0.303***
	(1.532)	(36.555)	(26.449)	(0.810)	(0.020)
PCT	-0.002	-2.215	-0.207	-0.179**	-0.000
	(0.004)	(1.745)	(0.234)	(0.072)	(0.000)
Intercept	-134.511	13749.386	3502.529*	338.071**	-4.884
	(203.683)	(10343.63)	(1912.715)	(135.249)	(3.679)
Fixed Effects	Y	Y	Y	Y	Y
N	16857	511	3239	2727	456
R2	0.014	0.033	0.126	0.026	0.390
Adjusted R2	0.012	0.019	0.122	0.022	0.380

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

The classification of geographical distribution can be based on the perspective of import production locations and import destinations. From the perspective of import destinations, import destinations can be divided into central regions, eastern regions, and southern regions according to their geographical

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locations. From the perspective of import production locations, they can be grouped according to the regional trade relations with China into the RCEP group, CEPA group, North America group, and Europe group. Due to the unique trade relations between the United States and China, the author further subdivides the North America group into the United States and Canada. Based on trade relations, the heterogeneity of the impact of social attention on the sales volume of imported products from different production locations is explored using grouped regression, and the following regression results are obtained.

From the empirical results of the regional heterogeneity analysis in the Table 2, import live streaming from different regional trade agreement areas is affected differently by social attention and other factors. Import live streaming from regions under the RCEP regional trade agreement is more easily influenced by communicativeness, interactivity, and followership. Import live streaming from regions under the CEPA regional trade agreement is more easily influenced by interactivity. Import live streaming from the United States is more easily influenced by communicativeness and interactivity. Import e-commerce live streaming from Canada is more easily influenced by interactivity and followership. Import live streaming from Europe is more easily influenced by interactivity. Looking at the commonalities of live streaming in different regions, the empirical results show that interactivity has a more universal impact on live streaming sales volumes, confirming the robustness of Conclusion 3.

In all regional sample groupings, interactivity has a significant positive effect on import sales volumes. This may be because for consumers, online comments from other consumers are more credible. The interactions between consumers and hosts, as well as among consumers themselves during live streaming, enhance the transparency and quality of the live streaming.

Another noteworthy result comes from Group (1) and Group (3) in Table 2 above. The results not only show the significant impact of social attention on sales volumes but also indicate that the main source countries of imported e-commerce live streaming products are RCEP countries and the United States. On the one hand, the RCEP regional trade agreement is a focal point of China's foreign trade development. On the other hand, the United States has always had a deep-rooted history with China's foreign trade. Despite the recent trade wars between China and the United States and the outbreak of the COVID-19 pandemic, which have slowed down China's foreign trade growth, it cannot be denied that deepening regional trade cooperation and improving Sino-US trade relations are crucial for promoting China's import trade development.

5. Conclusions

This paper summarizes and makes theoretical inferences on the four dimensions through which social attention affects the sales volume of imported e-commerce live streaming, based on a review of the literature and theoretical analysis. It also empirically analyzes the impact of communicativeness, identifiability, interactivity, and followership on sales volume using panel data. The empirical results show that identifiability, interactivity, and followership have a significant positive effect on live streaming sales volume. Among them, followership has the greatest contribution to increasing sales volume, followed by interactivity and identifiability. Communicativeness has the least and weakest contribution to increasing sales volume. The ranking of contributions based on the size of the variable coefficients can be expressed as followership - interactivity - identifiability - communicativeness. This is the opposite of Kotler's consumer behavior model, which progresses from awareness - interest - inquiry - action. This suggests that consumers who enter the next stage of the consumer behavior model during live streaming are more likely to make purchasing decisions. This may be because consumers in the action stage also have higher identifiability, interactivity, and followership, making them more inclined to purchase products promoted in live streaming.

From the perspective of merchants, increasing the communicativeness of live streaming does not significantly promote sales volume. Although consumers engage in spreading and watching behaviors, most users do not proceed to purchase the products promoted in the live stream but remain at the initial stage of consumer behavior. This may be because the live streaming content, products, and hosts fail to enhance consumers' identifiability, interactivity, and followership. Therefore, merchants should not only expand the reach of their live streams to stimulate consumers' interest in spreading and watching but also focus on highlighting product advantages and providing quality services to retain users.

The geographical distribution analysis of the import production countries of live streaming products reveals that users prefer imported goods from East Asia and North America. The impact of social attention on the sales volume of imported products in live streaming is heterogeneous. Products imported

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from member countries of the RCEP (Regional Comprehensive Economic Partnership) regional trade agreement are more likely to be affected by social attention in live streaming sales. Different export source countries and host locations may lead to different trade costs, which in turn affect product prices and consumer purchases. Moreover, the geographical distribution analysis of hosts shows that influential import e-commerce live streaming hosts are mainly located in Myanmar and northern China. The most important finding of the regional heterogeneity analysis is that it confirms the robustness of the significant positive effect of interactivity on live streaming sales volume.

The limitation of this study lies in the empirical methodology. The fixed-effects model employed in this research cannot eliminate the endogeneity issues within the model. Moreover, during the empirical research process, no suitable exogenous instrumental variables were identified. Given that interactivity has a significant impact on sales volume, the author envisions that a potential direction for further in-depth research could be based on text mining of the online comment content from imported e-commerce live streaming. This could explore the mediating effect of online word-of-mouth on interactivity and sales volume, as well as investigate the possible bidirectional causal relationships between sales volume and the dimensions of communicativeness, identifiability, interactivity, and followership within the research model.

References

[1] Mou, J., Zhu, W., & Benyoucef, M. (2020). Impact of product description and involvement on purchase intention in cross-border e-commerce. Industrial Management & Data Systems, 120(3), 567–586. https://doi.org/10.1108/IMDS-05-2019-0280.

[2] Yang, Q., & Lee, Y.-C. (2023). The effect of live streaming commerce quality on customers' purchase intention: Extending the elaboration likelihood model with herd behaviour. Behaviour & Information Technology, 42(5), 1–22.

[3] Liu, F. J., Meng, L., Chen, S. Y., & Duan, S. (2020). The Impact of Internet Celebrity Live Streaming on Consumer Purchase Intentions and Its Mechanism. Chinese Journal of Management, 17(1), 94–104.

[4] Park, H. J., & Lin, L. M. (2020). The effects of match-ups on the consumer attitudes toward internet celebrities and their live streaming contents in the context of product endorsement. Journal of Retailing and Consumer Services, 52, 101934. https://doi.org/10.1016/j.jretconser.2019.101934.

[5] Xu, Y., Jiang, W., Li, Y., & Guo, J. (2022). The Influences of Live Streaming Affordance in Cross-Border E-Commerce Platforms: An Information Transparency Perspective. Journal of Global Information Management, 30(2). https://doi.org/10.4018/JGIM.20220301.oa3.