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The Relationship between Streaming Hits View and Sales Performance in Live Streaming Commerce

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[Abstract]

This study aims to explore the relationship between product assortment, streaming airtime, streaming hits views, and sales performance, while examining the moderating effects of weekends versus weekdays. The data used for the analysis consists of 2023 live commerce streaming information provided by Labangba Data Lab. A PLS(Partial Least Squares) model was employed because all variables were measured using formative indicators. The key findings are as follows: First, product assortment positively influences streaming hits views. Second, streaming airtime has a negative impact on streaming hits views. Third, streaming hits views positively affect sales performance. Finally, a positive moderating effect of weekends and weekdays on the relationship between streaming hits views and sales performance was identified. The study concludes with a discussion of theoretical and practical implications.

▸ **Key words**: Live streaming commerce, Product assortment, Streaming airtime, Streaming hits view, Sales performance

[요 약]

이 연구는 제품 구성, 스트리밍 airtime, 스트리밍 조회수, 판매 성과 간의 관계를 탐구하고, 주말과 평일이 가지는 조절 효과를 분석하는 것을 목적으로 한다. 분석에 사용된 데이터는 Labangba Data Lab에서 제공한 2023년 라이브 커머스 스트리밍 데이터를 기반으로 한다. 모든 변수가 형성지표로 측정되었기 때문에 PLS(부분 최소 제곱) 모형을 사용했다. 분석 결과는 다음과 같다. 첫째, 제품 구성은 스트리밍 조회수에 긍정적인 영향을 미친다. 둘째, 스트리밍 airtime은 스트리밍 조회수에 부정적인 영향을 미친다. 셋째, 스트리밍 조회수는 판매 성과에 긍정적인 영향을 미친다. 마지막으로, 스트리밍 조회수와 판매 성과 간의 관계에서 주말과 평일의 조절 효과가 긍정적으로 확인되었다. 연구는 이론적 및 실무적 시사점을 함께 제시하고 있다.

▸ **주제어**: 라이브 스트리밍 커머스, 제품구색, 스트리밍 편성시간, 스트리밍 조회수, 판매 성과

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I. Introduction

Live streaming commerce is a retail format of selling products or services directly to customers through live video streaming. It can assist retailers, brands, and digital platforms in creating value and achieving value co-creation[1]. The value co-creation theory emphasizes creating customer experience value resulting from a series of interactive activities between consumers and companies[2]. Thus, live streaming commerce is a form of value co-creation and is providing new business opportunities.

Korea's live streaming commerce business began in 2020 and is expected to grow to 10 trillion won by 2023[3]. This is because the M.Z. generation, familiar with real-time video streaming due to the influence of YouTube and other platforms, has emerged as the leading consumer group[4]. Customers can learn more product or service information by interacting with streamers and other participants, thereby increasing the availability of purchasing and ultimately realizing value co-creation[5].

Live streaming commerce is a new retail format that satisfies customers' needs for convenience[6]. Large companies can build their live commerce system, while small and medium-sized businesses or small business owners can use a live commerce platform[4].

In previous studies on live streaming commerce, the influence relationship has been presented through surveys. How does this new retail format impact consumer behavior, such as purchase intention, loyalty, trust, and engagement?[7-10].

Social science methods for analyzing causal relationships include regression analysis or structural equation modeling based on surveys. These analysis methods are widely used in social sciences, and recently, there has been a trend of analyzing causal relationships using big data.

This study collects data from platform users of live streaming commerce and analyzes the relationships among product assortment, streaming airtime, streaming hits view, and sales performance.

II. Theoretical Background and Hypothesis

1. Live streaming commerce

The widespread adoption of live streaming has facilitated its integration into marketing campaigns and has fueled a boom in the e-commerce economy[11]. This phenomenon contrasts with relatively low purchase rates of such experiential products on traditional e-commerce platforms, where consumers feel highly uncertain[12]. On the other hand, in live streaming commerce, broadcasters can achieve huge sales by eliminating this uncertainty. For example, a famous broadcaster sold 15,000 lipsticks in just five minutes during a live streaming show. Most viewers have no hesitation in purchasing a product as long as the broadcaster recommends it. Live streaming is especially effective for introducing and selling experiential products such as clothing and cosmetics[13].

In Korea, many companies in various fields are building and operating live commerce platforms. That is, e-commerce companies such as Coupang, Gmarket, and 11st, large distributors such as Lotte, Shinsegae, TV home shopping companies, large portals such as Naver and Kakao, live commerce specialists such as Grip and Bogoplay, and delivery app Baedal Minjok are operating live commerce platforms. SNS companies such as YouTube, Instagram, and TikTok are also expected to enter the live commerce platform business[4].

Live streaming channels have become a popular direct selling channel, providing sellers with consumer interaction and engagement they have never experienced before[9]. It has evolved into a two-way direct sales channel for selling various products, from clothing and electronics to furniture, jewelry, and food[3].

2. Product assortment

A product assortment is the set of all products and items a particular seller offers for sale. A product assortment consists of various product lines. Its dimensions permit the company to expand its business, while consumers will be more satisfied with a more comprehensive range of products[14].

The idea is that greatly expanding the size of product options increases the variety of choices available to customers, thus increasing the possibility of selecting a product that suits their tastes, ultimately leading to consumer satisfaction and purchasing decisions. The logic is that providing a wide range of products is always important to stimulate consumers' need for variety[15]. Many studies have shown that the greater the variety of products, the more positive the purchase intention and satisfaction[16].

3. Streaming airtime and hits view

The most significant feature of live commerce streaming is that it complements the difficulties in real-time communication between sellers and consumers in T-commerce, S-commerce, and M-commerce, as well as the disadvantage of being unable to touch the products physically[17]. Live streaming commerce is gaining popularity because its dynamism, intimacy, presence, real-time nature, unexpectedness, interactivity, and entertainment fit the M.Z. generation's needs, which value individuality, fun, curiosity, satisfaction, and quick decision-making in purchasing activities[4].

According to a study by Seol[18], a channel with a large number of subscribers and an old YouTube channel does not necessarily have a high average view count, and even if a company dominates the ranking of popular channels, individual creators can increase the number of views depending on the genre. The number of YouTube subscribers and the elapsed time(after content posting) have also been identified as factors affecting the number of views on a channel[19]. However, only some people who has registered a YouTube channel with a video can generate a lot of views or revenue. About half of the videos registered on YouTube have less than 350 views, 90% have less than 11,000 views, and about 90% of the registered videos do not generate any revenue[20].

This study uses the airtime and number of hits view of live streaming commerce as variables affecting sales performance. Since there are few previous studies on this theme, the results of previous studies on YouTube, which are similar in form, are borrowed.

4. Sales performance

Among 2,282 live commerce broadcasts, the broadcast data is selected based on the criteria introduced above, and finally, 34 broadcast data are selected. The types of collected broadcasts have high views in various categories, and at the same time, there are sections where consumer response is high[21]. Subscriber count and view count are the criteria by which YouTube allows advertising revenue and are also indicators that many studies have used to gauge the popularity of a channel[22]. On YouTube, measuring economic performance indicators based on views makes sense, as consumer interest and behavior, such as views and continuous viewing, are converted into monetary revenue[23]. Therefore, increased live commerce views and positive consumer responses will likely lead to increased sales performance.

5. Weekend and weekday of broadcast date

This refers to the effect based on experience, such as different demand patterns depending on the week, with weekend sales being higher than weekday sales or department stores having the lowest sales on Mondays[24]. According to Nam's [25] study on the day-of-the-week effect using five years of data from the domestic men's clothing company 'P,' weekend sales are higher than weekday sales, and Sunday sales are significantly higher on weekends. Therefore, whether it is a weekend or not, the relationship between live streaming views and sales may be affected.

Based on the contents of the previous studies examined above, the following hypotheses are presented.

H1: Product assortment will have a positive effect on streaming hits view.

H2: Streaming airtime will have a positive effect on streaming hits view.

H3: Streaming hits view will have a positive effect on sales performance

H4: The impact of streaming airtime occurring on a weekend will moderate the relationship between streaming hits view and sales performance.

The purpose of this study is to present the research model, as shown in Figure 1, to examine the relationship and test the hypotheses regarding the effects of product assortment, streaming airtime, streaming hits view, and sales performance in live streaming commerce.

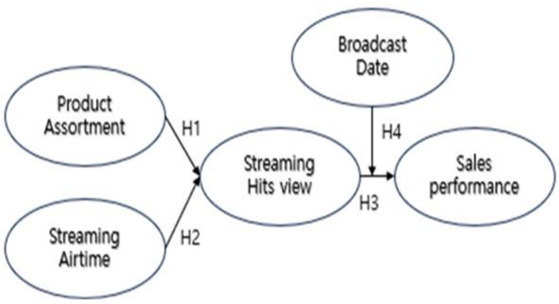

Fig. 1. Research Model

III. Method

1. Data collection and sample characteristics

Labangba Data Lab is a company that collects live commerce data generated from major domestic portals such as Naver Shopping LIVE, SSG Live, Kakao Shopping LIVE, etc., and shopping mall platforms in real-time and provides data necessary for ranking and statistics.

Live streaming data for each women's clothing category on each platform was collected for one year, from January 1, 2023, to December 31, 2023. A final sample of 9,938 streaming data was selected after excluding missing values, such as those selling products in other categories. The characteristics of the sample are shown in Table 1.

Live commerce focuses on enabling consumers to make purchase decisions in real time as they view the products being showcased. Selecting the right product assortment increases the likelihood that viewers will make a purchase during the broadcast, thereby boosting conversion rates. Product categories that encourage impulse buying tend to be particularly effective in this context[26].

The product assortment for each streaming channel ranges from a minimum of 1 to a maximum of 152. The streaming airtime is divided into morning/and afternoon, with 2,110 and 7,828 respectively. The streaming hits views range from a minimum of 8 to 455,064, and sales performance ranges from 1 to 15,301.

Table 1. Sample Characteristics

Construct	Number
Product Assortment	1~152(pcs)
Streaming Airtime	A.M.: 2,110, P.M.: 7,828
Streaming Hits View	8~455,064(times)
Sales Performance	1~15,301(volume)
Broadcast Date	weekday: 7,893, weekend: 2,045
Total	9,938

2. Analysis technique

The collected online live streaming commerce data contains several categorical variables, such as product category, broadcast date, and industry, so cross-sectional analysis is appropriate[27]. PLS is more appropriate since all variables are measured only by formative indicators, and this study is exploratory[28-29].

In this situation, PLS is particularly useful because it can handle complex relationships and does not assume that the indicators are highly correlated. Unlike covariance-based methods, PLS-SEM is well-suited for models with formative constructs, as it maximizes the explained variance of dependent variables, making it a robust choice for this type of data[30]. Therefore, this study conducts empirical analysis using the Smartpls 4.0 program.

3. Measurement

Five variables are used in this study and obtained from live streaming commerce data based on sixteen well-known platforms in Korea. The operational definitions of the variables used in this study, as shown in Table 2, are as follows. Product assortment refers to the number of product assortments sold per streaming. Streaming airtime is the streaming schedule time and is dummy processed by dividing it into am/pm times. Streaming hits view represents the number of views, which is measured by the number of views per streaming and used as a mediating variable. The broadcast date is a moderate variable as the programming date and is a dummy processed by dividing it into weekdays and weekends. These variables represent point-in-time information that occurs while consumers engage in live streaming commerce.

Table 3 presents the number of streaming data points for each variable, totaling 9,938, along with the minimum, maximum, average, and standard deviation(S.D.).

Table 2. Measurement

Construct	Measurement
Product Assortment	The number of products seller sell per streaming
Streaming Airtime	A.M: 0, P.M: 1
Streaming Hits View	Hits view per streaming
Sales Performance	Sales volume per streaming
Broadcast Date	Weekday: 0, Weekend: 1

Table 3. Descriptive Statistics

Descriptive Statistics					
	N	Minimum	Maximum	Average	S.D.
Product Assort ment	9938	1.00	152.00	21.1881	9.94306
Average of price	9938	4500.00	54381741.00	129235.8576	588053.98737
Hits view	9938	8.00	455064.00	11671.8750	31221.07624
Sales volume	9938	1.00	15301.00	126.6336	388.59430
Revenue	9938	1101700.00	2175269640.00	9130144.1595	33682677.31834
Valid N(by sample)	9938				

IV. Hypothesis Testing

1. Measurement model

All variables are measured as single items and are not on the Likert scale in Table 4. The formative index does not require reliability or internal consistency testing because it is assumed that there is no or low correlation between the variables[31].

As a result of testing for multicollinearity between variables, the VIF value is confirmed to be 1, indicating no problem in Table 4[32].

The fit of the measurement model can be evaluated using SRMR and NFI values. SRMR(standardized root mean square residual) is an absolute measure of goodness of fit. The measurement model of this study is considered to satisfy the model fit criteria with SRMR of 0.021 (0.08 or less) and NFI of 0.906 (0.9 or more)[33]. The R^2 value of the endogenous variables can evaluate the goodness of fit of the PLS structural model. R^2 values are classified as low (0.02 to 0.13), medium (0.13 to 0.26), and high (0.27 or higher). According to the R^2 value in Table 3, it is possible to conduct a significance test on the path coefficient. The R^2 value of this research model was confirmed to be 0.036 and 0.029.

In formative indicators, each indicator represents an independent factor, so the correlations between the indicators are expected to be low or non-existent. If the correlations are high, the appropriateness of the formative indicators may be questioned. Therefore, examining the correlations between the indicators can be used to assess discriminant validity in Table 5[29].

Table 4. Measurement Model

Construct	VIF	R^2
Product Assortment	1	
Streaming Airtime	1	
Streaming Hits View	1	0.036
Sales Performance	1	0.029
Broadcast Date	1	
NFI=0.906, SRMR=0.021		

Table 5. Discriminant Validity Analysis

	1	2	3	4	5	6
PA(1)	1					
SA(2)	0.005	1				
SHV(3)	0.187	-0.027	1			
SP(4)	0.004	-0.056	0.162	1		
BD(5)	0.025	-0.082	-0.027	0.003	1	
BT*HV(6)	0.055	-0.002	0.283	0.094	-0.075	1
PA: product assortment, SA: streaming airtime SHV: streaming hits view, SP: sales performance BD: broadcast date, BT: broadcast time, HV: hits view						

2. Results of structural model

This study used bootstrapping, a PLS path coefficient significance test method, to extract 10,000 random samples from live streaming commerce data and test statistical significance.

The results of the hypothesis test are presented in Table 6 and Figure 2. First, product assortment has a positive effect on streaming views, supporting H1(β=0.187, t=12.496, p<0.01). Second, streaming airtime has a negative effect on streaming hits view, so H2(β=-0.069, t=3.072, p<0.01) is rejected. Third, streaming hits view has a positive effect on sales performance, supporting H3(β=0.147, t=6.315, p<0.01). Fourth, as a result of analyzing the moderating effect of whether the broadcast date is a weekend on the relationship between streaming views and sales performance, H4 (β=0.19, t=2.176, p<0.05) is supported.

To reflect the revisions in Table 7, the VIF-inner model values are presented. The VIF-inner model is assessed to interpret the path coefficients (correlations between constructs), and it is considered that multicollinearity is not an issue even in the model with the moderating effect incorporated.

Table 6. The Results of Hypothesis Testing

Path		β	S.E.	t-value	p-value	Results
H1	PA→SHV	0.187	0.015	12.496	0.000	Accepted
H2	SA→SHV	-0.069	-0.070	3.072	0.001	Rejected
H3	SHV→SP	0.147	0.024	6.135	0.000	Accepted
Moderating Effect of Broadcast Date(weekend and weekday)						
	BT→SP	0.027	0.026	1.030	0.152	
H4	BT*SHV	0.190	0.087	2.176	0.015	Accepted
PA: product assortment, SA: streaming airtime SHV: streaming hits view, SP: sales performance BT: broadcast time, HV: hits view						

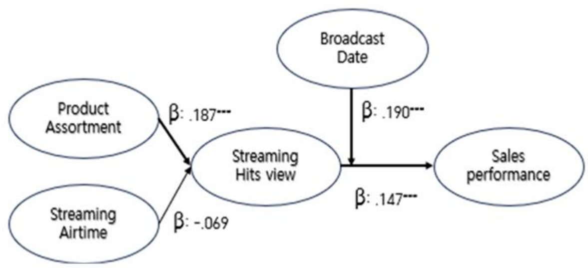

Fig. 2. Path Model

Table 7. Multicollinearity in the Model with the Moderating Effect Incorporated

VIF-Inner model	Hits view	Product Assortment	Sales Performance
Hits view			1.087
Product Assortment	1		
Sales			
Time slot	1		
Weekend dummy			1.006
Weekend dummy x hits view			1.092

V. Conclusions

This paper studies live streaming commerce, a marketing distribution channel. Unlike many previous studies based on questionnaires, this study analyzed consumer data using a live streaming commerce platform, and based on the results of the analysis, the following theoretical and practical implications are presented.

First, among the variables used in this research model, streaming hits view is a digital marketing indicator, and sales performance is a marketing financial indicator[34]. Seo and Yoh[35] used non-financial marketing indicators, such as attitude toward a purchase and intention to use fashion live streaming commerce(FLSC). They measured the attributes of FLSC, such as ease of use, economic efficiency, enjoyment, and interactivity, using a Likert scale.

Second, this study is meaningful in using product assortment and streaming airtime as antecedent variables of streaming hits view in live streaming commerce of women's clothing. Digital variables are used instead of the attitude measurement variables used in marketing as the antecedent variables. Yoo et al.[36] suggested that streaming is preferred when a song is of a singer with a lengthy career, a title track from an album, or frequently introduced on TV programs. Although there are previous studies on digital music streaming, there are few studies on the antecedent variables of the streaming hits view of women's clothing.

Third, this study analyzed the moderating effect of broadcast date(weekday and weekend) on the relationship between streaming hits view and sales performance, which adds to the significance of the study. Since women's clothing sales in live streaming commerce differ between weekdays and weekends, the analysis of this moderating effect may have implications.

Fourth, as the number of women's clothing product assortment increases, the number of streaming hits view increases. This suggests that the more diverse the range of women's clothing, whether in an offline or online store, the more searches there will be and the higher the likelihood of sales.

Fifth, the morning and afternoon streaming airtimes are treated as dummies, dividing them into 0 and 1, respectively, and the regression coefficients are confirmed to be negative. Our analysis found that live streaming during the morning hours has a more positive impact on streaming hits view. That is, when a seller wants to sell through live streaming, it can be inferred that women's clothing product lines are likely to see higher views if they schedule streaming during the morning hours.

Sixth, higher hits views of live streaming have a positive effect on sales performance. In various previous studies, the number of streaming hits view is known to affect performance[34, 37]. This means that the number of hits view for live commerce streaming is a measurement item that reflects the interest of actual users. Therefore, the number of the product assortment that shows the diversity of products and the number of hits view according to the broadcast time can directly affect the performance of live streaming sales.

Seventh, the interaction between weekdays, weekends, and the number of streaming hits viewed significantly affects sales performance, and the regression coefficient was confirmed to be positive. The results show that weekend live streaming hits view can improve sales performance. The sale of women's clothing through live streaming suggests that broadcasting on weekends rather than weekdays can help improve hits view and sales performance.

In South Korea, live commerce has rapidly gained popularity, driven by the integration of e-commerce with real-time video streaming and high consumer engagement. Compared to other countries like China and the U.S., China leads the market with large platforms such as Taobao Live, leveraging influencers and vast digital ecosystems to drive massive sales. The U.S. is gradually adopting live commerce, with major companies like

Amazon and Facebook entering the space, though consumer adoption is slower than in Asia.

For South Korean live commerce to expand internationally, several strategies could be effective. First, tailoring content and product offerings to fit the preferences and cultural nuances of target markets is essential. Second, collaborating with established platforms like Amazon or Alibaba can help Korean companies leverage existing infrastructures and customer bases. Third, utilizing the global popularity of K-pop, K-beauty, and Korean entertainment can help attract international audiences. Fourth, partnering with local influencers in foreign markets can boost credibility and appeal among local consumers. Fifth, ensuring efficient international shipping and customer support will enhance the overall consumer experience in new markets.

The future research directions that can be suggested through this study are as follows. First, it would also be meaningful to distinguish performance differences through comparative studies between subcategories within a product group. Second, it is necessary to consider the development of various formative indices not used in this study and the use of multi-item scales. Third, future research is needed to improve the lack of women's clothing live streaming commerce targeting in this study. Fourth, if streaming data from live commerce is accumulated in the future and multi-year data is collected, it is necessary to study it by platform size and product group.

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