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Human versus AI? Investigating the Heterogeneous Effects of Live Streaming E-commerce

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Completed Research

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Abstract

Live Streaming E-commerce (LSE) refers to a technology-enabled business model that embeds live streaming into e-commerce, where streamers sell products and interact with the viewers in real-time. When stores use human streamers, they benefit from high Synchronicity Interaction (SI), which causes users' engagement. However, when stores use artificial intelligence (AI) streamers to replace human streamers, it is unclear whether high SI human streamers are more effective than low SI AI streamers at selling products. This study examines drivers of whether AI streamers are more or less effective at selling products than human streamers. We find that human and AI streamers perform differently, and product categories moderate this effect. Our results contribute to the LSE and business value of AI literature and offer insight to platforms and stores seeking to better leverage AI technology and technology designers interested in developing more effective AI streamers.

Keywords: Human versus AI streamers, Product category, Live streaming e-commerce, Business value of artificial intelligence, Media synchronicity theory.

Introduction

Live streaming e-commerce (LSE) is a technology-enabled business model that embeds live streaming in online shopping platforms, where streamers sell products through broadcast and interact with the viewers in real-time (Cai et al., 2018). In contrast to conventional online shopping, where customers search and compare products by themselves and make decisions based on product descriptions, ratings, and reviews, viewers on LSE exchange information with the streamers. LSE has rapidly grown in global popularity. In March 2020, over 265 million Chinese users actively engaged in LSE, and the value of China's LSE market increased 280% between 2017 and 2020, and is expected to reach $423 billion by 2022. Taobaolive.com is one example of a popular live streaming e-commerce platform in China, with a domestic market share of 35 percent (McKinsey, 2021). It has also gained popularity in the United States and Europe on platforms such as Twitch (Mediakix, 2017; Zhao et al., 2021).

The unique feature of LSE is the real-time interaction between streamers and viewers. For example, streamers demonstrate product materials and functions through video. In the meantime, viewers can click likes to show interest or leave comments through the chatbox, such as questions or concerns about the products. Streamers provide answers immediately upon seeing the comments. These unique real-time interactions shape LSE users' diverse intentions. Prior live streaming literature explains that these synchronicity interactions satisfy viewers' motivation for social interaction, entertainment, information seeking, etc. (Hilvert-Bruce et al., 2018).

As LSE has boomed, so has companies' investment in streamers. For example, Taobaolive.com has created 1.5 million jobs, and the number of streamers grew by 661 percent from 2019 to 2020. Along with increasing numbers, streamer type has diversified. Whereas early streamers were often selected for their physical beauty, firms have started picking streamers for their notoriety, leading to more significant revenue. For example, in 2019, Taobaolive recruited 200 celebrity streamers. In 2020, these human streamers proved capable, with over 1000 livestream rooms generating more than $14.5million in revenue per room (Alibaba, 2021).

Although human streamers' real-time interactions can support viewers' social and entertainment motivation and lead to significant economic gains, they also have potential challenges. On the one hand, critical characteristics of streamers, such as personality traits and emotions, have proven to have positive and negative effects on their popularity and economic performance (Lin et al., 2021; Zhao et al., 2021). On the other hand, human streamers' service capability is constrained by the overwhelming need for interactions with viewers, especially in LSE – one or two streamers need to introduce around 50 products, answer questions, engage with thousands of million viewers in one show (L. Wang et al., 2021). Under such intense attention, live streaming accidents, mistakes, and missteps, such as misstating a price, are unavoidable.

Because human streamers are expensive and their performance is challenging to predict, stores have explored AI as an alternative LSE salesperson. For example, Alibaba Group has made deep investments in AI streamer technology to support LSE. AI streamers cost less than 10 dollars per day, can work 24 hours plus seven days a week, and never feel fatigued (Hu et al., 2021). Furthermore, benefitting from advanced natural language technologies, AI streamers can track viewers' comments constantly and give answers without dismissing them. The robust knowledge base enables AI streamers to precisely answer product-related questions. More importantly, AI streamers are highly controllable. Viewers can ask AI streamers to introduce the products they want to know instead of following human streamers' streaming flow. Clearly, compared to human streamers, AI streamers are much cheaper than humans and more reliable and precise to a certain degree.

However, AI streamers also have limitations. For example, AI streamers struggle to engage with questions outside of pre-defined topics. While they offer basic functionality (e.g., introducing products, saying hello to viewers, and answering code-in questions), AI streamers lack the ability to offer rich, synchronous user interaction commensurate with that provided by human streamers (Hu & Ming, 2020).

Comparing the performance of human and AI streamers are essential because of their financial implications for LSE platforms and stores. If decision-makers understand when AI streamers are equally or more effective than human streamers, they can better decide when and how to use them to support LSE. Moreover, it is essential because AI agents have been studied in healthcare, finance, and human resource disciplines (Acemoglu & Restrepo, 2020; Dixon et al., 2021; Esteva et al., 2017; Geetha & Bhanu, 2018; Qi, 2018), we lack an understanding of drivers of their effectiveness in dynamic, interactive social situations such as LSE. As a result, we empirically compare human and AI streamers' performance and examine boundary conditions on their effectiveness. Specifically, we explore these questions:

1. Whether human and AI streamers have different streaming performances?

2. What factors moderate the effectiveness of human and AI streamers?

To answer our questions, we assembled a unique dataset to compare human and AI streamers' performance in real-world conditions. We collected observational data from Taobaolive.com and conducted general regression analyses to examine whether human and AI streamers differed in streaming performance (sales, sale amount, per price) and viewers' engagement (the number of views, thumbs, comments, and increased fans). Then, we further investigate product categories to test whether they moderate streamers' performance by conducting a subgroup analysis. We found that human streamers dominantly perform better than AI streamers in viewers' engagement and some streaming performance (sales, sale amount), while AI streamers perform better in per price. When considering product categories, human streamers perform comparably to AI streamers in apparel and fashion, beauty, food, and furniture, and AI streamers perform better in consumer electronics in per price. For the other product categories, human streamers perform better than AI streamers.

This study contributes to the growing literature on LSE and AI. First, it enhances the literature on LSE and the business value of AI. Second, it generates guidelines for store managers regarding whether they should and how to obtain value from AI streamers. In addition, it provides design guidelines for AI LSE providers to consider requirements for using AI streamers across product categories.

Literature review and conceptual background

Live Streaming E-commerce (LSE)

Live streaming e-commerce is a subset of e-commerce embedded with real-time interaction, a unique feature for the live streaming (Cai et al., 2018). It allows streamers to conduct a real-time live show to demonstrate products and guide shopping. Viewers can send comments such as concerns and questions through the chatbox. Streamers can answer the viewers' questions and interact with viewers in real-time (Li et al., 2021).

Previous LSE research has focused on the users' motivation and behaviors. Scholars have examined LSE viewers' motivations for seeking social support and entertainment (Cai & Wohn, 2019; Cai et al., 2018), factors driven by customers' trust and engagement (Hu & Ming, 2020; Wongkitrungrueng & Assarut, 2020), user stickiness (Li et al., 2021) and popular characteristics of streamers (Zhao et al., 2021). However, most prior studies focus on live streaming and pay less attention to LSE, which is the value created by using a consumption-driven platform (Chen et al., 2019).

Recently, two studies have focused on the economic perspective of LSE, which examined how real-time sales analytic data impact sales performance and whether streamers collaborating with AI-assistant can drive viewers' purchase behavior (He et al. 2021; Wang et al. 2021). Our research can enrich the previous LSE literature by investigating the business value of artificial intelligence applications in LSE.

Business Value of Artificial Intelligence (AI)

Artificial intelligence refers to the applications of a computer or a robot to do human-like tasks requiring human intelligence, including learning, understanding, and interacting (Rai et al., 2019). AI applications have become a pervasive societal, technology, and business phenomenon (Li, 2021). Research has investigated the benefit of AI across fields. AI could help doctors increase their diagnostic accuracy (Esteva et al., 2017). Studies in human resources investigated the performance of AI in the recruitment (Acemoglu & Restrepo, 2020; Dixon et al., 2021; Geetha & Bhanu, 2018). Several studies test the effect of voice AI on consumer purchase behavior; disclosure of AI would reduce purchase rate (Luo et al., 2019; Sun et al., 2019).

Recently, one study examined whether collaboration between human streamers and AI-assistant can drive viewers' purchase behavior (L. Wang et al., 2021). However, there is no research about how AI performs when they independently conduct selling tasks under LSE channels. Our study contributes to this literature by offering insight into when and how to use AI to create business value for firms pursuing LSE.

Media Synchronicity Theory (MST)

The Media Synchronicity Theory (MST) helps explain how humans and AI streamers' effectiveness could differ in how they manage the communication process, notably information transmission and information processing. MST-based research has found that when communications quality is higher, stores realize more online transactions (Ou et al., 2014). Moreover, when online shopping websites offer high interactive control (low synchronicity), they create cognitive involvement. In contrast, websites with reciprocal communication (high synchronicity) lead to affective involvement, and increased involvement leads to high purchase intention (Jiang et al., 2010).

MST-based research suggests that synchronicity should shape LSE's ability to shape information transmission and speed up information processing. When human streamers offer High Synchronicity Interaction (High SI), which means human streamers can address viewers' comments in real-time and encourage viewers to engage with streamers synchrony, they are likely to generate more information processing (verification, adjustment, and negotiation) and engagement (viewers, thumbs, and comments). For example, when human streamers try on clothes, they would ask viewers to share their height and weight to provide customized size recommendations better; human streamers also would encourage streamers to leave comments in the chatbox to evaluate viewers' engagement.

In contrast, AI streamers offer viewers Low Synchronicity Interaction (Low SI), which means AI streamers can only address questions within their knowledge base, if the questions are out of AI streamers' ability, viewers must ask for help from consumer services. In addition, AI streamers lack the ability to encourage viewers to engage with them, and they are more like an active search tool that viewers can enter their questions to get answers from AI streamers. In this way, AI streamers may be better at information transmission since AI streamers can provide required information to viewers, instead of asking viewers to follow their streaming pace. Furthermore, with the advanced AI technology, AI streamers can provide multiple sources of information to viewers, such as voice descriptions of products, pictures of products, and applied scenarios. Because of advanced comments tracking technology, AI streamers can address all the comments without dismissing any of them and give a precise and comprehensive answer.

We apply MST in the LSE context and examine whether high and low synchronicity could explain streamers' effectiveness in persuading shoppers to purchase. We argue that human and AI streamers should differ in their streaming performance because they have different abilities to transmit information and foster understanding. Considering these differences in human and AI streamers' features, we posit that human streamers (High SI) are better at fostering information processing of experience goods because they leverage synchrony to ensure buyers understand they share and have a chance to negotiate with viewers (Dennis et al., 2008) while AI streamers (Low SI) are better for information transmission, especially for search goods that can be described in more objective, accurate terms. These differences should help to explain whether a streamer is more or less efficient at selling products and engaging with viewers.

Product Categories

In this study, we classify products into apparel and fashion, beauty, consumer electronics, food, and furniture. According to the McKinsey report (McKinsey, 2021), apparel and fashion (35.6%), beauty (7.6%), food (7.4), consumer electronics (4.6%), and furniture (3.6%) are the top 5 product categories, and apparel and fashion is the leading category in live streaming channels. On the other hand, Product categories have been proved to affect consumers' requirements for information and information process (Franke et al., 2004; Jiang et al., 2010; Ou et al., 2014). Specifically, some products (such as experience products) require more comprehensive verification, adjustment, and negotiation to help users access the product quality, which they cannot discover its quality before using it, while some products (such as search products) need the information collected from diverse sources and faster decision making since these products are easy to access quality by viewing collected information (Y.-Y. Wang et al., 2021).

Research Model and Hypotheses

Research Model

Our research model suggests that human streamers (High SI) and AI streamers (Low SI) differ in their ability to affect streaming performance (see Figure 1). We also posit that product categories (apparel and fashion, beauty, food, consumer electronics, and furniture) should moderate streamers' impact on streaming performance and viewers' engagement.

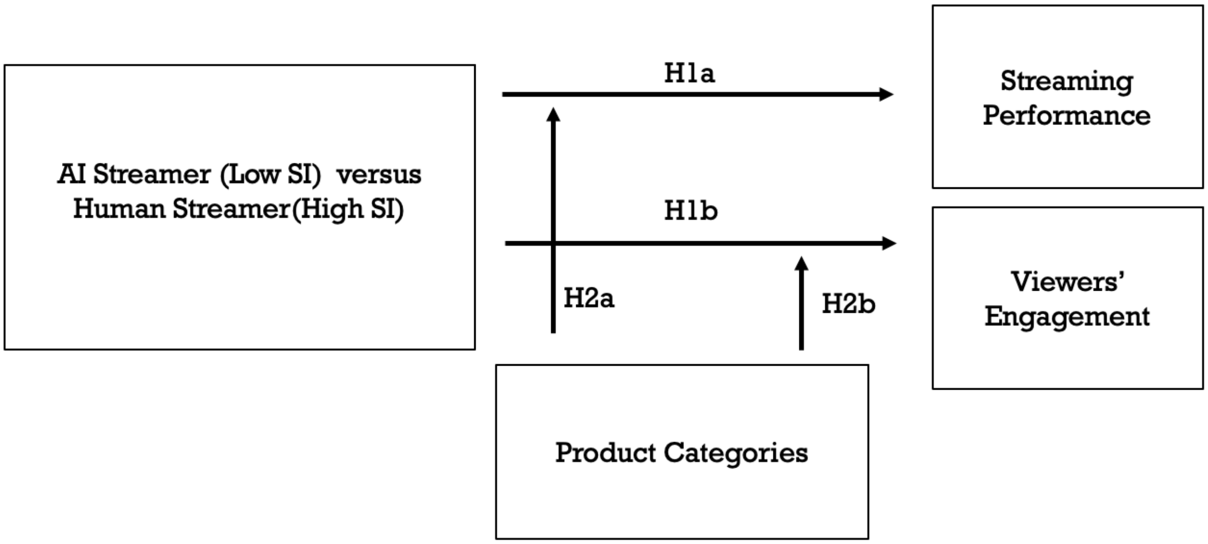

Figure 1 Research Model

Hypotheses development

Human streamers demonstrate products vividly in the video, share their own experience, answer viewers' comments upon seeing them, and encourage viewers to leave comments, which are likely to generate more information processing (verification, adjustment, and negotiation) and engagement (viewers, thumbs, and comments). In this process, streamers interact and negotiate with viewers and change their sale strategies to satisfy viewers' customized requirements and achieve a deal. In contrast, advanced AI technology such as natural language processing, text-to-speech function, automatically tracking, and mining context offers a robust knowledge base that enables AI streamers to provide functionality (e.g., introducing products, saying hello to viewers, and answering code-in questions) to satisfy viewers' information collection requirements. Furthermore, while AI streamers introduce products, images or videos of the products showing their application scenarios are also displayed on the same screen (Hu et al., 2021). All above functions provide multi-resources of information about a product, facilitating information transmission and further encouraging users' purchase behavior (Hu et al., 2021; Jiang et al., 2010). Hence, we propose:

H1a: Human streamers and AI streamers have different streaming performance.

LSE is not only a shopping platform. It also combines social interaction features from live streaming platforms. The theory of uses and gratifications has been applied to investigate LSE users' motivation that users have hedonic and utilitarian motivation, which indicts viewers who watch live streaming videos anticipate social support and entertainment (Cai et al., 2018). In addition, based on MST theory, human streamers (High SI) compared to AI streamers (Low SI) have the advantage of performing reciprocal communication with viewers to cause engagement (Dennis et al., 2008). Hence, we propose:

H1b: Human streamers can better encourage viewers' engagement compared to AI streamers.

Product category likely impacts consumers' information transmission and processing. When consumers purchase products – experience products, which means the consumer cannot discover the product quality before purchase (Nelson, 1970), consumers prefer to gather more information and conduct a comprehensive evaluation (Y.-Y. Wang et al., 2021; Zaichkowsky, 1985). Human streamers (High SI) are good at helping viewers understand information through high synchronicity interactions with viewers, which could provide an experience simulation (Huang et al., 2009). While different from experience goods, search goods, consumers can access the product quality before purchasing (Nelson, 1970), consumers prefer to obtain primary and essential ideas from multiple information resources. AI streamers (Low SI) have the advantage of providing accurate, concise, and various resources information (text, pictures, and videos) (Jing, 2011). Hence, we propose:

H2a: Human streamers perform better in experience products compared to AI streamers.

H2b: AI streamers perform better in search products compared to human streamers

Data and Analysis results

Our dataset was obtained from Taobaolive.com. The data contain 37,077 live streaming shows randomly drawn from 286 streamers from September 2021 to Jan 2022. Our unit of analysis is show-level. For each show, we collected data such as sales (sales value and volume, per customer transaction), engagement (number of thumbs, comments, views, and increased fans), duration, and streamer-level information (whether they are brand's streamers or not, the average number of fans, view, and thumbs in past three months). Table 1 summarizes the variables, and Table 2 provides descriptive statistics of those variables.

Variables	Definition
Show-level data	
Sales	The sales value for a show
Streamer_type (ST)	If the streamer is AI streamer, streamer_type =1; Otherwise, streamer_type =0
Num_view (NV)	the number of views during a show
Num_products (NP)	the number of products introduced in a show
Per_price (PP)	Per customer transaction
Sale_amount (SA)	The number of sold products for a show
Duration	The time length of a show
Num_thumb (NT)	The number of thumbs received for the a show
Num_comments (NC)	The number of comments received for a show
Num_increased_fans (NIF)	The number of increased fans for a show
Streamer-level data	
Fans	The number of fans the streamer has
Brand	If the streamer is employed by a brand, brand =1; Otherwise, brand =0
Sum_num_thumb (SNT)	The total number of thumbs received for the streamer in past 3 months
Sum_num_view (SNV)	The total number of view received for the streamer in past 3 months

Table 1 Summary of Variable

Variables	Obs.	Mean	St.d.	Min	Max	Median
NV	37,077	105,632	470,233	2	20,804,040	20,851
NP	37,077	86	73	0	500	56
PP	37,077	675	1,443	0	51,900	224
SA	37,077	4,206	29,619	0	2,840,297	333
Sales	37,077	1,394,866	10,692,970	0	607,887,600	76,968
Duration	37,077	10	6	0	35	10
NT	37,077	36,588	266,009	0	28,136,520	25,657

NC	37,077	3,263	5,911	0	96,268	1,237
NIF	37,077	709	2,079	0	52,041	204
Fans	286	6,248,437	6,208,767	123,953	45,354,810	4,353,765
SNT	286	1,698,161	3,623,923	4,964	32,787,870	695,371
SNV	286	5,576,668	11,177,300	21,946	79,968,490	1,943,319

Table 2 Descriptive Statistics for Variables

We use regression and sub-group analysis to test our hypotheses. First, we use sales, sale amount, and per price as dependent variables to measure the streamers' show performance. At the same time, we use human or AI streamers as our dependent variable. Because human and AI streamers represent High SI and Low SI, respectively, we want to see how these two types of synchronicity media affect viewers' communication process. Third, for the moderating variables, we use product categories: apparel and fashion, beauty, food, furniture, and consumer electronics. Finally, we run the regression on the full sample to see whether human and AI streamers perform differently and compare their performance in different product categories. Our regression analysis controlled for week-level and store-level fixed effects. Furthermore, to get a robust result, we also controlled for the streamers' number of fans, views, thumbs in the past three months, each show's duration, number of products, and per price. The results are shown in Table 3.

		Streaming performance			Viewers' engagement			
Treatment	Obs.	LS	LSA	PP	LV	NT	NC	NIF
All	37077	-1.4***	-1.4***	66.1***	-2.1***	-43384.3***	-2770.9***	-755.1***
Apparel and fashion	13296	-1.1***	-1.2***	-22.0	-1. 9***	-59353.3***	-3150.5***	-397.2***
Beauty	14004	-1.1***	-1.2***	-0.1	-2.0***	-44660.8+	-2433.6***	-573.4***
Consumer electronics	4873	-1.1***	-1.1***	359.8**	-1.9***	-41976.7***	-3639.9***	-575.4***
Food	3775	-1.0***	-1.3***	17.5	-2.0***	-19771.3***	-2080.4***	-520.3***
Furniture	1129	-1.7***	-1.8***	-0.1	-2.4***	-47136.0***	-1914.5***	-276.6***
Date		yes	Yes	yes	yes	yes	yes	yes
Store		yes	yes	yes	yes	yes	yes	yes
Note. reference level: human streamers + p<0.1, ** p<0.01, *** p<0.001								

Table 3 Results of Regression

Note: + p<0.1, ** p<0.01, *** p<0.001; for the human versus AI streamers, we use human streamers as the reference level; for simplicity, we only report the coefficient of human versus AI streamers and its p-value significance level in Table 3.

We found that human streamers yield better streaming performance and viewers' engagement than human streamers. This finding is consistent with the notion that human is better at helping LSE viewers convey information such as product attributes precisely and fulfill users who want to make a purchase decision. When we took a more granular approach and investigated product categories, we found human streamers and AI streamers have no differences in apparel and fashion, beauty, food, and furniture in terms of per price, but AI streamers perform better in consumer electronics in per price. We speculate that this difference is due to consumer electronics, which are search products that viewers can access the product quality before purchase and can collect information from other resources; thus, human streamers' high synchronicity does not necessary for viewers to make their purchase decision.

Discussion, Limitations, and Implications

Consistent with MST, we found that high synchronicity media (human streamers) are better at engaging with viewers by increasing information processing through retrospective communication and achieving purchase agreement by providing better information understanding. These different effects are moderated by product categories. When viewers purchase search products such as experience products, human streamers might perform better than AI streamers by sharing their experiences and enabling the experience simulation (Huang et al., 2009).

A limitation of this research is the observational dataset, where we were unable to control the viewers' intentional choices as to whether to watch human or AI streamers. This selection bias might systematically affect our results. Our next step is to design lab experiments to control external variables to further explore the underlying mechanism.

For practice, our findings suggest that managers should carefully consider which streamers to use in a shopping channel, especially when they operate a time-limited offering, such as LSE, where viewers need to make their shopping decision during the session. When managers want to sell experience products, such as apparel and fashion, food, and furniture, they should employ human streamers who provide a vicarious learning chance for viewers to gain five sensory inputs (i.e., touching, smelling, tasting, seeing, and hearing) and makes the shopping experience analogous to offline shopping scenarios. When managers want to sell search products (such as electronics), managers can adopt AI streamers whose primary purpose is to provide accurate product and promotion information to facilitate viewers' purchase decisions.

For research, our findings suggest a need for future work focusing on understanding when human streamers perform better than AI, particularly when considering stores' popularity. It would be helpful to assess how to develop AI that performs as effectively as human streamers in encouraging engagement, such as the number of views, thumbs, comments, and increased fans. Another future work is how to make use of human and AI streamers to help stores improve store-level. Taobaolive.com initiated a store-level evaluated policy that uses streaming frequency and duration, number of views, and sales to grade stores and provide different priorities based on stores' level, such as traffic guidance, priority advertisement display, and new AI-assistant technology support, etc. In addition, it remains to explore whether the number of fans would affect human and AI streamers' respective performance. Our study focuses on brand-run stores. Most of them are well-known brands and have a significant fans base already. More work is needed to explore how human and AI streamers perform for new stores or small stores.

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