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Artificial Intelligence (AI) Assistant in Online Shopping: A Randomized Field Experiment on a Livestream Selling Platform

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Abstract. Livestream technology enriches consumers' online shopping experience, enabling streamers to demonstrate products in real time while interacting with a large number of consumers for product sales. However, tension arises between streamers' constrained service capacity and consumers' individual service demands on livestream selling platforms. Streamers can only handle a finite number of interactions and inquiries because of time and capacity constraints, whereas consumers expect immediate, tailored responses. In this work, we examine whether and how an artificial intelligence-powered streaming assistant (termed "AI streaming assistant"), which helps consumers with interactive chat-based support for information acquisition and processing, can mitigate this tension in livestream selling. We report a randomized field experiment on a leading livestream selling platform, where the consumers in the treatment group had access to an AI streaming assistant during livestream sessions and the control group did not. Our results reveal that implementing an AI streaming assistant increases sales by 3.00% and reduces the product return rates by 12.55%. Our exploration of plausible mechanisms suggests that access to an AI streaming assistant increases consumers' perception of intelligent information provision (and, in parallel, interruption), which in turn reduces (and increases) uncertainty in decision making. Overall, the benefits of the AI streaming assistant's intelligent information provision outweigh its interruptions, subsequently increasing consumers' purchase intention and decision-making confidence. We also differentiate and explore two distinct modes of human-AI interaction, AI's proactive and reactive interactions, and our correlational results show that these interaction modes reinforce each other in increasing purchases and reducing product return rates. This study contributes to the literature on human-AI interactions, livestream selling, and product returns in online commerce. Our findings also provide actionable implications for online commerce platforms in designing and implementing AI artifacts.

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Keywords: livestream selling • artificial intelligence (AI) • AI streaming assistant • human-AI interaction • product return • randomized field experiment

1. Introduction

Livestreaming refers to an online media activity in which streamers host live broadcasts and interact with viewers (Zhao et al. 2021).[1] An important application of livestreaming is livestream selling, which has revolutionized online commerce worldwide (McKinsey Digital 2021).[2] eMarketer reports that livestream selling generated over $514 billion in revenue in China in 2022.[3] An industry survey found that approximately one in three U.S. consumers as well as one in four UK consumers had experience purchasing products via livestream selling.[4] Compared with other shopping platforms,[5] a key characteristic of livestream selling is its facilitation of intensive, real-time social interactions between streamers and viewing consumers (Hilvert-Bruce et al. 2018, Feng et al. 2024). For example, thousands or even millions of consumers can watch a streamer's product presentation and post live comments and questions during a livestream session (Hu and Ming 2020, Feng et al. 2024). Streamers often intersperse their product presentations with responses to live questions and make impromptu adjustments based on audience needs, inquiries, and feedback (Wohn et al. 2018). Additionally, streamers in livestream selling showcase products rapidly and strategically convey a sense of urgency and limited availability (McKinsey Digital 2021, Lo et al. 2022). Consequently, livestream selling prompts consumers to make impulsive, on-the-spot purchase decisions (Lo et al. 2022, Feng et al. 2024).

Although livestream selling enables streamers to engage in real-time interactions with large audiences (Lin et al. 2021, Pan et al. 2022), it also cognitively burdens streamers (Zeng et al. 2020). Because of time and attention constraints, streamers typically provide general product information in livestream selling and they can't respond to each consumer individually, at scale, thereby creating a tension between serving large audiences and providing individualized services in real time. Consumers often have to actively search for decision-related information across various sources, independently integrating that information to support their final decisions. A few livestream selling platforms have introduced virtual assistants powered by artificial intelligence (hereafter referred to as "AI streaming assistants") to ease this tension. Building upon speech recognition and natural language processing technologies, the AI streaming assistant has the ability to process a large volume of relevant information from multiple sources and generate integrated responses. It can provide pertinent, intelligent, and personalized information services to consumers via a chat-based interaction initiated by AI or consumers, thereby improving consumers' shopping experiences. However, AI streaming assistants may divert consumers' attention away from the streamer, potentially interrupting their streaming experiences and negatively impacting purchase in subsequent stages. Therefore, it is important to investigate how an AI streaming assistant shapes consumers' shopping experiences and outcomes in livestream selling, particularly its impacts across different stages of the purchase funnel.

Furthermore, AI streaming assistants may also influence product returns. In livestream selling, product return rates are substantially higher than in conventional online commerce.[6] Such high product returns can be attributed to immersive, real-time social interactions during livestream, which intensify emotional contagion (Lin et al. 2021), leading to irrational purchase decisions (Lee and Chen 2021). Additionally, streamers often introduce products at a rapid pace with selective information provision (McKinsey Digital 2021, Lo et al. 2022), which may result in consumers making decisions they later regret. AI streaming assistants intelligently recognize each consumer's information needs and provide real-time services to reduce uncertainty in decision making, thereby supporting consumers in making high-quality purchase decisions. Thus, we seek to understand whether AI streaming assistants can reduce product return rates in livestream selling. Bearing the above in mind, given the urgent need to understand the effects of AI streaming assistants in livestream selling, we aim to answer the research questions: *How do AI streaming assistants in livestreaming impact purchases and returns?*

We report a large-scale randomized field experiment conducted by a leading livestream selling platform in Asia (hereafter referred to as "the partner platform"). During the experiment, consumers were randomly assigned to one of two groups: a treatment group with access to an AI streaming assistant in livestream selling sessions and a control group without such assistance. Our analysis yields several findings. First, deploying the AI streaming assistant increases product purchases by 3.00% in the treatment group compared with the control group. Second, the presence of an AI streaming assistant leads to a significant decrease in product return rates by 12.55%. Third, our exploration of the underlying mechanisms via an online experiment reveals that the implementation of AI streaming assistants significantly enhances consumers' perception of intelligent information provision, which in turn reduces uncertainty in decision making. Meanwhile, the implementation of AI streaming assistants also increases consumers' perception of interruption that has a positive effect on perceived uncertainty. Taken together, the advantages of the AI streaming assistant's intelligent information delivery surpass its interruptions, increasing consumers' purchase intention as well as decision-making confidence. Finally, we distinguish two types of human-AI interaction modes, AI's proactive and reactive interactions, and provide correlational evidence showing that consumers who engage in both interaction modes exhibit more purchases and have lower product return rates than those in the control group.

Our study makes several contributions to the related literature. First, our study adds to the literature on human-AI interactions (Huang and Rust 2018, Tong et al. 2021) by elucidating how the AI streaming assistant facilitates consumers' information acquisition and processing in the livestream selling context. Our study is among the first work to document how to leverage AI technologies in facilitating one-to-many, human-to-human interactions. Second, our research adds to the emerging literature on livestreaming (e.g., Cheng et al. 2020; Hu and Ming 2020; Wang et al. 2021a) by examining the role of AI streaming assistants in livestream selling. AI streaming assistants reduce uncertainty in consumer decision making by providing intelligent, individualized, real-time information services, thereby alleviating the tension between streamers' service capacity and consumers' service demands in livestream selling. Third, this work offers meaningful insights into how an AI streaming assistant as a novel information technology (IT) artifact affects consumers' entire decision-making journey, particularly return outcomes in the postevaluation stage, which have been underexplored in previous research (Janakiraman and Ordóñez 2012, Rao et al. 2014). Our study documents the AI streaming assistant as an effective solution in addressing the product return issue in the livestream selling context, wherein buyers are susceptible to impulsive purchases.

Our findings also offer actionable managerial implications for livestream platforms, demonstrating the economic value of AI assistants in livestream selling and providing quantitative evidence for platforms to invest in AI development as a growth strategy. Further, we find that AI streaming assistants are particularly helpful for products with high uncertainty and for streamers with a large audience size; thus, livestream platforms can encourage consumers to interact with AI streaming assistants when buying products with high uncertainty and help streamers with a large audience size to leverage AI streaming assistants in serving consumers.

2. Related Literature

2.1. Livestreaming and AI

Our study is closely related to the literature on livestreaming, particularly in the context of livestream selling. Previous research primarily focuses on two main areas: (i) the economic value of livestreaming and (ii) how livestreaming characteristics affect consumer engagement and consumption (Sjöblom and Hamari 2017, Wohn et al. 2018, Pan et al. 2022). In examining the economic value of livestreaming, prior research suggests that integrating livestream selling as a sales channel boosts product sales (Cheng et al. 2020, Hu and Ming 2020). Streamers enhance purchases by using strategic content delivery narratives (Wang et al. 2021a), visual merchandising (Guo et al. 2021), and targeted selling approaches (Guo et al. 2021), leading viewers to engage in hedonic consumption or make impulsive purchases (Lin et al. 2021). Meanwhile, prior studies suggest that viewers participate in livestreaming for various reasons, including information seeking, emotional attachment, entertainment, and, importantly, real-time social interactions (Sjöblom and Hamari 2017, Hilvert-Bruce et al. 2018, Wohn et al. 2018). Additionally, factors such as streaming interactions (Hou et al. 2020, Xue et al. 2020), emotions (Lin et al. 2021), viewer group size (Lu and Chen 2021, Zhao et al. 2022), and streamer characteristics (Lu and Chen 2021) significantly influence viewer engagement and consumption. Notably, the intensive, real-time service demands from a large audience challenge streamers' service capacity (Zeng et al. 2020), as they cannot provide personalized interactions for all viewers and have to dismiss most service requests.

In the video streaming context, prior research suggests that AI can optimize the adaptive delivery of high-quality video streaming services for viewers (Menkovski and Liotta 2013). AI's capability also includes providing personalized viewer experiences at scale, catering to heterogeneous viewer preferences (Wang et al. 2021b). Further, research by the British Broadcasting Corporation (BBC) has shown that AI can assist with video production tasks to expand the coverage of live events (Wright et al. 2023). Whereas previous work focused on AI usage in backend content production and innovative content delivery, our study examines viewer-facing AI technologies, improving our understanding of the real-time chat-based interactions between consumers and AI streaming assistants in livestream selling. This work also contributes to the broader literature on livestreaming by investigating how AI streaming assistants balance consumer service demands and streamer service capacity, intelligently providing information services that cater to consumers' personalized needs and supporting them in reducing uncertainty in decision making.

2.2. Consumer's Decision-Making Process and Product Return

Our research also speaks to the literature on consumer decision-making processes. Prior research has demonstrated that consumers follow a visit-to-purchase funnel to make purchase decisions (Huang et al. 2019, Bar-Gill and Reichman 2021, Gopalakrishnan and Park 2021). Initially, in the *awareness* stage, consumers become aware of a product and decide whether to visit the product website (Hoban and Bucklin 2015, Li et al. 2019). Upon visiting, consumers enter the *consideration* stage, actively searching for product information to reduce uncertainty and possibly adding products to their shopping carts (Gopalakrishnan and Park 2021). Then comes the *evaluation* stage in which consumers assess related information and may decide to purchase (Huang et al. 2019). With the availability of individual-level clickstream data, recent studies have explored factors influencing consumer decisions at different stages, such as advertising strategies (Ho et al. 2020, Todri et al. 2020), coupon designs (Gopalakrishnan and Park 2021), and word-of-mouth system implementation (Huang et al. 2019). Our study adds to this body of work by elucidating how AI streaming assistants influence consumer decisions in each stage of the purchase funnel in livestream selling.

More importantly, after purchasing a product, consumers reevaluate their choices in the postpurchase stage and make product return decisions. Product returns are a critical challenge for e-commerce platforms, particularly in the context of livestream selling, where buyers are prone to impulsive purchases (Lin et al. 2021, Feng et al. 2024). Product returns during the postpurchase stage remain an understudied area in the literature (Petersen and Kumar 2009, Sahoo et al. 2018), partially because of reasons like limited access to individual-level product return data or endogeneity concerns. Previous research has explored factors influencing product returns, such as online reviews (Minnema et al. 2016) and real-time social interactions (Feng et al. 2024). Analyzing data from a randomized field experiment, our study advances this stream of work by evidencing AI streaming assistants as an effective antecedent in influencing the entire consumer decision-making process, as well as the postpurchase stage of product returns.

2.3. Human-AI Interaction

Our study advances research on human-AI interaction, especially in providing personalized, impromptu service to support consumers' information acquisition and processing through chat-based interactions. According to Cui et al. (2022), automation and intelligence are two unique abilities that AI has. AI cannot only automate simple and repetitive tasks but also facilitate smarter or intelligent control of how related tasks are performed (Cui et al. 2022). Prior research has shown that, enabled by advanced algorithms and big data, AI can make accurate predictions and provide real-time responses at scale (Huang and Rust 2018, Agrawal et al. 2019). Additionally, AI excels in the accuracy of language translation (Brynjolfsson et al. 2019), work instructions (Sun et al. 2022), and quality predictions (Senoner et al. 2022). Advanced AI algorithms also enable companies to achieve a higher level of customization, such as generating personalized feedback (Tong et al. 2021), personalized services (Huang and Rust 2018), and targeted marketing strategies (Kumar et al. 2019). Research also suggests that AI is suitable for tasks in contexts coping with heterogeneous instances (Deng et al. 2023). While interacting with AI, individuals' perception of intelligence positively affects their expectation confirmation of AI (Moussawi and Koufaris 2019) and intention to use or continuously use AI (Moussawi and Koufaris 2019, Moussawi et al. 2023, Ling et al. 2025).

Our study extends the literature on human-AI interaction by investigating how the provision of the AI-supported chat-based information acquisition and processing influences consumers in making purchase decisions and how these interactions affect subsequent postpurchase return rates in livestream selling. We provide empirical evidence from a randomized field experiment and further explore the plausible underlying mechanisms through an online experiment. We also consider different human-AI interaction modes, namely, AI's proactive and reactive interactions, and provide correlational evidence on how these factors shape outcomes.

3. Hypothesis Development

In the livestream selling context, streamers interact with consumers in a one-to-many format, publicly interacting with all viewers. Because of their constrained capacity, streamers cannot respond to every consumer comment (Zeng et al. 2020, Tong et al. 2021), and they often selectively address common questions and overlook idiosyncratic service needs (Tong et al. 2021). To optimize selling performance, streamers introduce and promote products at a rapid pace (McKinsey Digital 2021, Lo et al. 2022) and use selling strategies like emphasizing product benefits or scarcity to induce quick purchase decisions (Feng et al. 2024). As a result, consumers in livestream selling mainly receive product information strategically delivered by streamers and they have to actively search for decision-related information across various sources when watching livestreams, independently integrating the collected information to support their decisions.

Artificial intelligence, built on technologies such as natural language processing and speech recognition, can process a large volume of relevant information from multiple sources and generate intelligent, tailored responses, acting "intelligently" in service provision (Yang et al. 2021). AI as a streaming assistant can understand consumer comments reasonably well and offer relevant information. Unlike human streamers, an AI streaming assistant is not limited by capacity constraints (Sun et al. 2021, Tong et al. 2021). It can offer information services to consumers during livestreams via chat-based interactions in a separate one-on-one communication thread, catering to individual needs (Huang and Rust 2018). More importantly, by automatically tracking consumers' informational needs, an AI streaming assistant can actively provide timely information services accordingly. Prior research suggests that timely information and synchronous communication can help increase online retail purchases (Tan et al. 2019, Sun et al. 2021). Additionally, following the information theory (De et al. 2013), the evaluative information from streamers can be complemented by real-time information from AI streaming assistants, which facilitates product evaluations and reduces uncertainty.

As noted by Pavlou et al. (2007), consumer perceptions of uncertainty in online environments often deter them from engaging in online transactions. Consumers are generally risk-averse, and uncertainty about a product leads to heightened perceptions of risk, such as concerns that the product might not meet their expectations or fears of financial loss (Mitchell 1999). According to the literature on behavioral economics, losses loom larger than gains (Kahneman and Tversky 1979). If consumers are uncertain about a product's value or performance, the fear of losing money or experiencing dissatisfaction often outweighs the perceived benefits of purchasing (Kahneman and Tversky 1979), thereby lowering their purchase motivation. By actively providing timely and individualized information services, the AI streaming assistant effectively reduces this uncertainty during the decision-making process. As a result, it plays a crucial role in enhancing consumer confidence, mitigating perceived risks, and increasing product sales. Therefore, we propose the following hypothesis.

Hypothesis 1a. *The implementation of an AI streaming assistant during streaming sessions increases the number of purchases in livestream selling.*

However, introducing an AI streaming assistant could potentially interrupt the flow experience for consumers during livestream sessions. According to the flow theory, a flow state represents a mental state in which a person is fully immersed and focused on a single activity (Nah et al. 2011). In the livestream selling context, factors such as the social presence of other consumers, live social interactions, and the real-time engagement strategies by the streamer can stimulate consumers' flow experience, which positively influences consumption intention (Li and Peng 2021). Prior studies have demonstrated that external interruptions triggered by alerts, notifications, or environmental cues can interfere with users' flow state, adversely affecting their attention and experience, leading to abandonment of their current activities (McFarlane 2002, Adler and Benbunan-Fich 2013). In our research context, an AI streaming assistant transforms the typical one-to-many consumer-streamer interaction mode, where numerous consumers simultaneously watch a livestream session to receive information. By actively providing services through chat-based interactions, the AI streaming assistant shifts consumers' attention from watching streamers' live performance to engaging in one-on-one conversations with the AI, thereby interrupting consumers' livestream experiences (Nah et al. 2011). Such interruptions could disturb consumers while they are receiving important information from streamers, particularly information that arouses consumer interest in products, thereby increasing consumers' perception of uncertainty and reducing their motivation to make purchases. Thus, we propose the following competing hypothesis.

Hypothesis 1b. *The implementation of an AI streaming assistant during streaming sessions decreases the number of purchases in livestream selling.*

Next, we hypothesize about the potential impact of an AI streaming assistant on product return rates. Livestream selling has been subject to high product return rates (Feng et al. 2024), partly because consumers in a livestream selling environment often make rash purchases based on information provided by streamers, who tend to emphasize product benefits and strategically persuade consumers to make quick decisions (Feng et al. 2024). Consequently, the information delivered by streamers may not support consumers in fully evaluating the products (De et al. 2013, Feng et al. 2024). Consumers themselves need to search for decision support information from various sources, which is a time-consuming and effort-intensive process. Excessive energy expenditure often leads to incomplete information acquisition or the inability to make high-quality decisions (Jacoby 1984, Laker et al. 2018). In contrast, the introduction of an AI streaming assistant enables timely and proactive information services whenever consumers have information needs. Through continuous one-on-one interaction with the AI, consumers can obtain integrated and processed detailed information directly from the AI, ensuring consumers keep their focus on decision making. Therefore, as an effective supplement to streamers, the AI streaming assistant changes consumers' information acquisition and processing mode in supporting consumers collecting thorough information to reduce uncertainty in the decision-making process and improve the quality of decisions, thereby decreasing the likelihood of consumers returning purchased products (De et al. 2013). Hereby, we propose the following hypothesis:

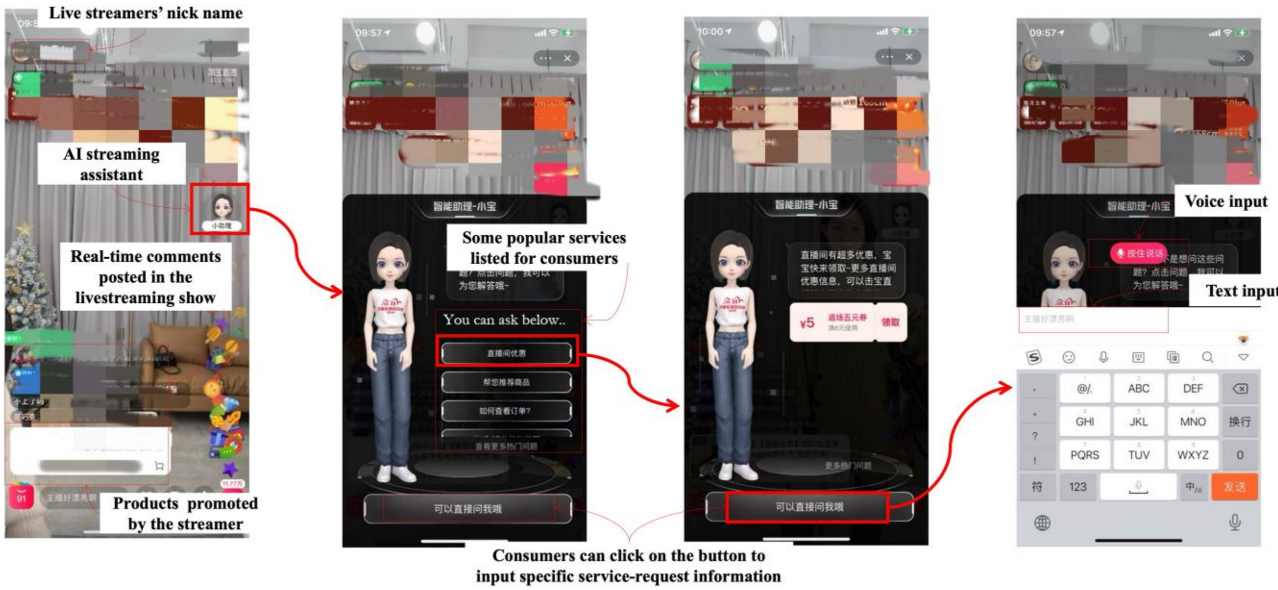
Hypothesis 2. *The implementation of an AI streaming assistant during streaming sessions decreases product return rates in livestream selling.*

4. Research Context, Randomized Field Experiment, and Data

4.1. Research Context and Field Experiment

The research context of our study is the livestream selling business unit of a leading e-commerce platform in Asia.[7] Built on speech recognition and natural language processing technologies, the AI streaming assistant continuously tracks consumer comments to intelligently detect their service needs during livestream selling sessions. It can process a vast amount of related information from various sources, such as product details from the product web page, return and exchange policies on the seller website, and price discounts in a livestream room, to generate appropriate responses. The AI streaming assistant is displayed as an icon in the virtual streaming room's user interface (UI). When the AI streaming assistant recognizes common consumer requests like product information, coupons, or orders, it waves its hand and displays the message "I can answer your question" under its icon. Consumers can also directly tap the icon to engage in a private, one-on-one thread interaction with the assistant, as it will pop up to provide popular services learned from service records, such as available coupons, product recommendations, and order tracking

Figure 1. (Color online) The UI for an AI Streaming Assistant



assistance. Apart from these popular services, consumers can also engage in text or voice conversations with the AI streaming assistant. Figure 1 shows the UI design of the AI streaming assistant in our study.

To understand the effectiveness of the AI streaming assistant, we report a randomized field experiment from the partner platform. The experiment, employing a between-subjects design, lasted five days and was conducted from February 19 to 24, 2021. The partner platform systematically executed individual-level randomization.[8] Each consumer was randomly assigned to either the treatment or control group and remained in the assigned group throughout the experiment. The key distinction between the two groups is that consumers in the treatment group can see and interact with the AI streaming assistant during livestream sessions, which serves as an intelligent agent that monitors and understands consumers' needs and proactively addresses them. In contrast, consumers in the control group cannot see or interact with the AI streaming assistant in any livestream session during our experiment.[9] Figure 2 illustrates the experimental design, and Figure B1 in Online Appendix B outlines the experiment flow.

4.2. Data, Variables, and Randomization Checks

Our partner platform provided a random sample of 132,199 consumers in the experiment,[10] with 65,902 consumers in the treatment group and 66,297 in the control group. The data set includes consumers' archival information, such as account registration dates and the number of streamers followed by each consumer before the experiment. We also observe consumers' historical digital traces on the platform, including the

Figure 2. (Color online) Experimental Design

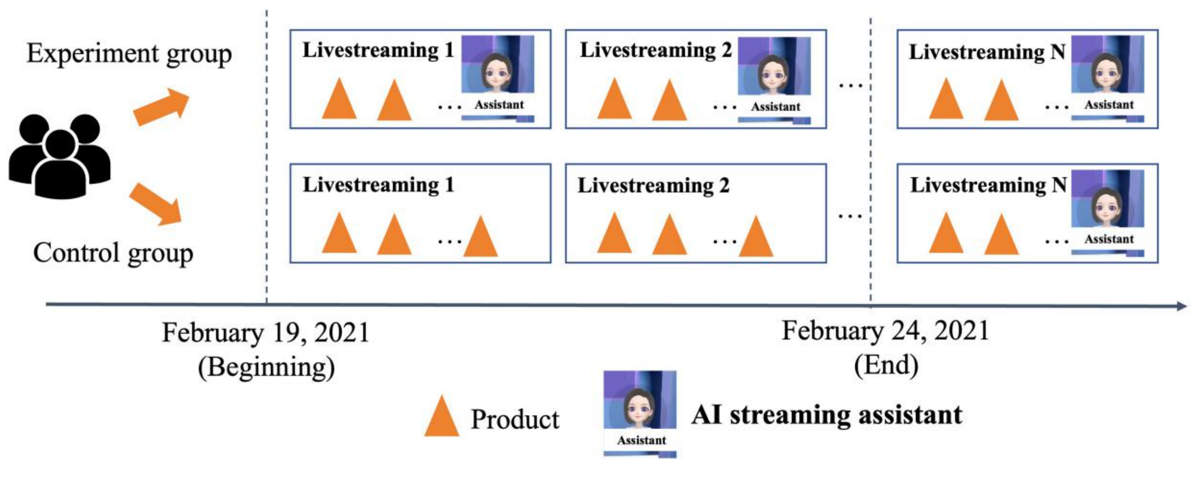


Table 1. Description of Variables

Variable	Description
Treatment	If a consumer is assigned to the treatment group, *Treatment* = 1; otherwise, *Treatment* = 0
Tenure	The number of years since a consumer registered an account
VIP Level	The consumer levels defined by the partner platform
# Followed Streamers	The number of streamers a consumer followed before the experiment
# Watched Livestreams	The number of livestream sessions a consumer watched one month before the experiment
Live Duration	The total time a consumer spent on watching livestream selling within one month before the experiment
# Purchased Products	The number of items a consumer bought through livestream one month before the experiment
Livestream Spending	The total amount of money a consumer spent on livestream selling within one month before the experiment
# Click	The number of times that a consumer clicked products in livestream selling during our experiment
# Cart	The number of times that a consumer added products to the shopping cart in livestream selling during our experiment
# Pay	The number of times that a consumer placed orders in livestream selling during our experiment
Consumer Spending	The amount a consumer spent in livestream selling during our experiment (normalized)[a]
Return Rate	The proportion of returned items among the products purchased during the field experiment

[a]Because the partner platform does not allow the revelation of consumer spending data in livestream sessions, it normalized the prices of products paid by consumers in our data set. The partner platform normalized order prices by dividing the product prices by the highest product price in livestream sessions during our experiment. For example, if two consumers purchased products during our experiment, one consumer purchased products with prices as 1 and 1, and the other consumer purchased products with prices as 10, 2, and 5. The normalized results are 0.1, 0.1, 1, 0.2, and 0.5. We calculated *Consumer Spending* for each consumer as 0.2 and 1.7.

number of livestream sessions watched and the number of items bought in livestream sessions in the month preceding the experiment. Additionally, the data set covers product items returned among the products purchased during livestream selling sessions in the experiment. We also collected clickstream data, detailing consumer actions like clicking product links, adding products to the cart, and placing orders. Tables 1 and 2 present variable descriptions and descriptive statistics, respectively.

We perform randomization checks with granular measures at the consumer, streamer, and livestream levels, respectively. The pairwise *t*-test results in Tables 3–5 show that all observable covariates do not significantly differ, confirming the comparability of the treatment and control groups.

Table 2. Descriptive Statistics

Variable	Min.	Max.	Mean	Std. Dev.
Treatment	0	1	0.499	0.500
Tenure	5	15	11.268	1.425
VIP Level	2	8	4.594	1.322
# Followed Streamers	0	1,331	226.962	232.843
# Watched Livestreams	2	4,441	214.609	431.408
Live Duration	2.316	100,132.600	2,217.701	5,208.248
# Purchased Products	0	2,974	16.175	104.747
Livestream Spending	0	434,919	811.679	4,232.977
# Click	0	2,397	39.435	76.452
# Cart	0	195	1.157	3.467
# Pay	0	130	0.931	2.580
Consumer Spending*	0	2.260	0.002	0.017
Return Rate	0	1	0.038	0.155

Notes. Because of the nondisclosure agreement (NDA) with the partner platform, we do not observe the raw or descriptive data on transactional variables (marked with *), such as consumer spending and returns. The partner platform normalized the value of these variables.

Table 3. Randomization Checks at the Consumer Level

Variables	Treatment group, mean (SD)	Control group, mean (SD)	p-value
Tenure	11.268 (1.422)	11.270 (1.427)	0.840
VIP Level	4.198 (1.324)	4.191 (1.321)	0.345
# Followed Streamers	227.734 (233.894)	226.194 (231.792)	0.229
# Watched Livestreams	213.738 (429.392)	215.474 (433.403)	0.465
Live Duration	2,205.266 (5,161.562)	2,230.063 (5,254.255)	0.387
# Purchased Products	15.991 (102.547)	16.359 (106.890)	0.523
Livestream Spending	816.293 (4,106.932)	807.092 (4,354.684)	0.692

5. Analyses and Results

5.1. Main Analyses

We employ regression analyses, specified in Equation (1), to estimate the effects of AI streaming assistants on outcomes.[11]

$$\mathit{Outcome\ Variable}_i = \beta_0 + \beta_1\,\mathit{Treatment}_i + \varepsilon_i, \qquad (1)$$

where $\mathit{Outcome\ Variable}_i$ indicates the outcomes of interest and $\mathit{Treatment}_i$ is a binary variable that indicates a consumer's group assignment. In livestream selling contexts, purchase events are infrequent because of generally low conversion rates. Given the large proportion of zero values for our outcome variables, # *Click*, # *Cart*, and # *Pay*, we perform zero-inflated Poisson regressions to obtain accurate estimations of the effects of our experimental treatment on these outcomes (Fávero et al. 2021).

We report the regression results in Table 6. Columns 1 and 2 suggest that the implementation of an AI streaming assistant does not significantly affect the number of product clicks ($\beta = 0.0081$, $p > 0.1$) nor the frequency of adding products to shopping carts ($\beta = 0.0052$, $p > 0.1$). However, the AI streaming assistant leads to a 3.00%[12] increase in the number of orders placed by consumers in livestream selling ($\beta = 0.030$, $p < 0.05$). Further, column 4 shows a significant positive effect of the AI streaming assistant on consumer spending ($\beta = 0.00023$, $p < 0.01$), representing a 10.95%[13] increase. These findings indicate that the implementation of an AI streaming assistant significantly enhances consumer purchases in livestream selling, supporting Hypothesis 1a, while not supporting its competing hypothesis Hypothesis 1b.

Next, we examine the effect of the AI streaming assistant on consumers' postpurchase decisions, specifically, product return rates, and present the results in columns 6 and 7 of Table 6.[14] Our analysis shows that consumers in the treatment group have lower return rates than those in the control group ($\beta = -0.139$, $p < 0.05$), resulting in a 12.55%[15] reduction in the return rates (see column 6, Table 6). As a robustness check, we applied coarsened exact matching (CEM) to improve the comparability of samples in both the treatment and control groups, and the regression in column 7 yields a consistent result ($\beta = -0.140$, $p < 0.05$). Thus, we conclude that the AI streaming assistant can significantly reduce product return rates in livestream selling, supporting Hypothesis 2.[16]

We perform additional analyses to check the robustness of our findings. First, following Chen et al. (2017) and Pu et al. (2022), we use bootstrapping to validate the reliability of our main results. Specifically, we replicate our regressions with samples augmented with the Bayesian bootstrap method using the EXBSAMPLE package in STATA. As presented in Table E1 in Online Appendix E, the bootstrapped sample results are

Table 4. Randomization Checks at the Streamer Level

Variables	Treatment group, mean (SD)	Control group, mean (SD)	p-value
Multichannel network (MCN)	0.094 (0.292)	0.093 (0.290)	0.756
Account Level	3.446 (0.618)	3.440 (0.622)	0.518
# Followers*	0.006 (0.026)	0.006 (0.026)	0.822
# Livestreams*	0.118 (0.077)	0.118 (0.077)	0.901
Live Duration*	0.201 (0.210)	0.200 (0.211)	0.713
# Sold Products*	0.0009 (0.016)	0.0010 (0.017)	0.737
Sales*	0.0005 (0.015)	0.0007 (0.017)	0.712

Notes. MCN measures whether a streamer belonged to an official streamer company before the experiment; Account Level captures the streamer levels defined by the partner platform before the experiment; # Followers measures the number of followers a streamer has before the experiment; # Livestreams measures the number of livestreams a streamer has within the month before the experiment; Live Duration measures the accumulated time a streamer spent on streaming within one month before the experiment; # Sold Products measures the number of products a streamer sold within one month before the experiment; Sales measures the amount of money all consumers spent in a livestream room within one month before the experiment. Because of the NDA, we cannot observe the raw or descriptive data on certain variables (marked with *). The partner platform normalized the values of these variables to prevent disclosure of the raw data.

Table 5. Randomization Checks at the Livestream Level

Variables	Treatment group, mean (SD)	Control group, mean (SD)	*p*-value
# Streamed Item	46.439 (48.344)	46.317 (48.293)	0.775
# New Follower*	0.0009 (0.0117)	0.0009 (0.0117)	0.990
# Visits*	0.0013 (0.0135)	0.0013 (0.0136)	0.966
# Consumers*	0.0006 (0.0109)	0.0006 (0.0110)	0.978

Notes. # Streamed Item measures the number of product types introduced in a livestream session during our experiment; # New Follower measures the number of new followers a livestream session attracted during our experiment; # Visits measures the number of accumulated consumer visits in a livestream session during our experiment; # Consumers measures the number of distinct consumers who watched a livestream session during our experiment. Because of the NDA, we cannot observe the raw or descriptive data on certain variables (marked with *). The partner platform normalized the values of these variables to prevent disclosure of the raw data.

consistent with our main analyses. Additionally, we replicate the regression analyses at the transaction level with livestream session fixed effects and consumer fixed effects. The results, reported in Table E2 in the Online Appendix, remain consistent with our main findings. Furthermore, given that consumers' product return decisions are contingent upon their purchase decisions, following Aggarwal et al. (2012) and De et al. (2013), we employ a two-stage Heckman probit model to test the robustness of the findings. The results in Table E3 in Online Appendix E confirm that the implementation of an AI streaming assistant significantly improves consumers' likelihood of purchase and reduces the probability of product return. In order to check the robustness of the effects of AI streaming assistants on Clicks, Carts, and Purchases, we also test our models on alternative specifications including Poisson regressions and ordinary least squares (OLS) regressions. We find consistent results, and the results are presented in Table E4 in Online Appendix E.

5.2. Exploration of Plausible Mechanisms

5.2.1. Online Experiment. We conduct an online experiment to explore the plausible mechanisms underlying the AI streaming assistant's impact on consumers in livestream selling. Participants, recruited from public universities in China, first recalled their livestream shopping experiences over the last year and were then asked to imagine a shopping experience on a livestream selling platform. They were then randomly assigned to either the control group, which watched a standard livestream selling video, or the treatment group, which viewed a livestream selling video that included scenes of the AI streaming assistant interaction and information services. Participants then rated their perceptions of the shopping experience in the video, regarding intelligent information provision (grounding on information theory (De et al. 2013)), interruption (based on flow theory (Nah et al. 2011)), uncertainty (Pavlou et al. 2007, Dimoka et al. 2012), purchase intention, and decision-making confidence on a seven-point Likert scale adapted from prior literature.[17] Afterward, they provided demographic information and received a \$1.40 (10 RMB) compensation. Table F1 in Online Appendix F lists the items and references of our measures. Figure F1 in Online Appendix F illustrates the flow of the online experiment.

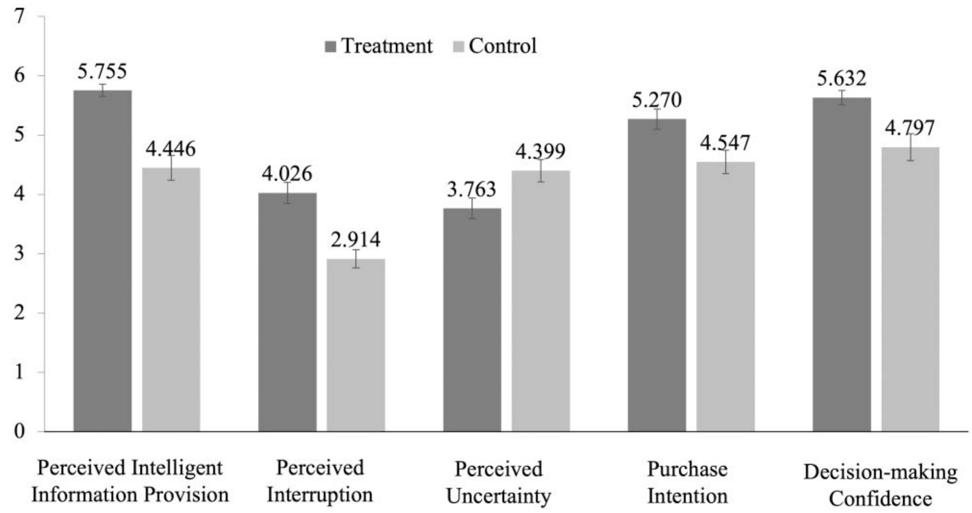
We analyze the data of 150 participants.[18] First, we conduct *t*-tests to compare participants' demographic characteristics and find no significant differences across the treatment and control groups, suggesting comparability. Next, we test and find high reliability and validity of measurement items in the experiment, as reported in Table F2 in Online Appendix F. We then compare the main variables, and the *t*-test results show that participants in the treatment group (versus control group), who watched the livestream selling video with scenes of the AI streaming assistant, perceived a higher level of intelligent information provision ($M_{treatment} = 5.755$ versus $M_{control} = 4.446$, $p < 0.01$), a higher level of interruption ($M_{treatment} = 4.026$ versus $M_{control} = 2.914$, $p < 0.01$), and a lower level of

Table 6. Effects of an AI Streaming Assistant on Clicks, Carts, and Purchases

	(1) # Click (zero-inflated Poisson regression)	(2) # Cart (zero-inflated Poisson regression)	(3) # Pay (zero-inflated Poisson regression)	(4) Consumer spending (OLS)	(5) Log (consumer spending) (OLS)	(6) Return rate (GLM)	(7) Return rate (GLM after CEM)
Treatment	0.0081	0.0052	0.030**	0.00023**	0.00098***	−0.139**	−0.140**
	(0.0102)	(0.0155)	(0.015)	(0.00009)	(0.00038)	(0.056)	(0.059)
Number of observations	132,199	132,199	132,199	132,199	132,199	35,164	32,344

Note. GLM, general linear model.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

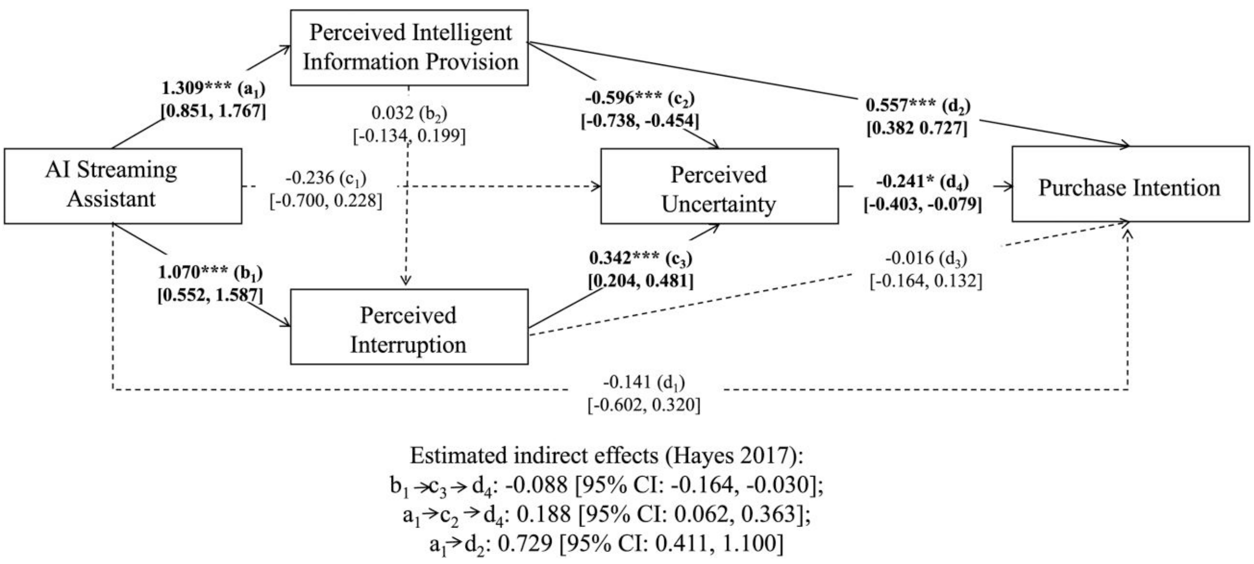
Figure 3. Mean Comparison Results of the Online Experiment



uncertainty ($M_{treatment} = 3.763$ versus $M_{control} = 4.399$, $p < 0.05$), and reported greater purchase intention ($M_{treatment} = 5.270$ versus $M_{control} = 4.547$, $p < 0.01$) as well as decision-making confidence ($M_{treatment} = 5.632$ versus $M_{control} = 4.797$, $p < 0.01$). We report the bar chart of the mean comparison results in Figure 3.

We then conduct sequential mediation analyses to understand potential mediation relationships, using the PROCESS model 6 with 5,000 bootstrap samples (Hayes 2017). Figure 4 shows the estimated coefficients and indirect effects on purchase intention. The results suggest that the paths of *AI Streaming Assistant → Perceived Intelligent Information Provision → Perceived Uncertainty → Purchase Intention* and *AI Streaming Assistant → Perceived Intelligent Information Provision → Purchase Intention* are both significant and positive. These findings suggest that the AI streaming assistant improves consumers' purchase intention by increasing their perception of intelligent information provision and reducing uncertainty. Meanwhile, as shown in Figure 4, we also find a negative indirect effect of *AI Streaming Assistant → Perceived Interruption → Perceived Uncertainty → Purchase Intention*. The result suggests that the AI streaming assistant may interrupt consumers while they are receiving information from streamers, which leads to increased uncertainty in decision making, and negatively affects consumers' purchase intention. That said, the total effect, combining the positive and negative effects, from *AI Streaming Assistant* to *Purchase Intention*, remains significant and

Figure 4. Sequential Mediation Effects on Purchase Intention



Note. Estimated indirect effects (Hayes 2017): $b_1 \to c_3 \to d_4$, −0.088 (95% confidence interval (CI): −0.164, −0.030); $a_1 \to c_2 \to d_4$, 0.188 (95% CI: 0.062, 0.363); $a_1 \to d_2$, 0.729 (95% CI: 0.411, 1.100).

positive, aligning with the results observed in the field experiment.[19] In terms of the effect of the AI streaming assistant on decision-making confidence, we also find similar results and we illustrate the results in Figure G1 in Online Appendix G.

5.2.2. Heterogeneity by Product Uncertainty. Here, we further explore the effect heterogeneity by product uncertainty, defined as the extent to which consumers are uncertain about the quality or suitability of products (Hong and Pavlou 2014). As indicated in the online experiment, where uncertainty reduction emerged as a plausible mechanism, the AI streaming assistant's impact on outcomes would be more salient for products with a high level of uncertainty. Product uncertainty is typically greater for products that lack sufficient information, such as online reviews (Mudambi and Schuff 2010, Tunc et al. 2021). In the field experiment, new products, which are introduced without any prior sales records, reviews, or ratings, present higher uncertainty. Thus, we categorize new products as high-uncertainty products whereas those with at least one sales record are categorized as other products. We then analyze the number of clicks, add-to-carts, purchases, consumer spending, and product return rates. The results in Table 7 show that the AI streaming assistant's effects on the subsequent outcomes are most evident in high-uncertainty products (panel A), rather than other products (panel B), providing suggestive evidence on uncertainty as a plausible mechanism.

5.2.3. Heterogeneity by Streamer Popularity. Next, we examine the effect heterogeneity by streamer popularity, measured by the number of followers a streamer had before the field experiment. On the partner platform, popular streamers typically have a large follower base, leading to higher viewership for their livestream sessions. Therefore, the tension between streamers' constrained service capacity and consumers' individual service demands in livestream selling is more severe for popular streamers. The AI streaming assistant could play a more salient role in influencing outcomes for streamers with larger audiences, where the demand-service capacity tension is greater. In our analysis, we distinguish popular streamers from other streamers based on the median number of followers that streamers had before the field experiment. We then analyze the number of clicks, add-to-carts, purchases, consumer spending, and product return rates for consumers who watched livestreams from popular and other streamers, respectively. The results, presented in Table 8, show that the AI streaming assistant's effects on the subsequent outcomes are most evident for popular streamers (panel A), rather than other streamers (panel B), indicating the AI streaming assistant's role in addressing the tension between streamers' capacity constraint and consumers' individual service needs.[20]

5.3. Additional Analysis of the Consumer-AI Interaction Mode

We explore providing some correlational evidence on the effects of different interaction modes between a consumer and the AI streaming assistant. In our study context, consumers can interact with the AI streaming assistant in two main ways: *reactive* or *proactive* interaction. Reactive interaction occurs when a consumer initiates interaction with the AI streaming assistant by tapping its icon on the screen.[21] Because consumers actively seek out services from the assistant, we consider this mode of interaction as the AI's being *reactive*. In contrast, proactive interaction occurs when the AI streaming assistant identifies and responds to consumers' service needs. The AI streaming assistant constantly monitors consumer comments during the livestream, seeking cues that indicate typical service requests (e.g., coupons, product information, or order assistance). When it detects service needs, the assistant notifies its availability by waving its hand on the screen with a message that reads "I can answer your

Table 7. Effects of the AI Streaming Assistant by Product Uncertainty

	(1) # Click (zero-inflated Poisson regression)	(2) # Cart (zero-inflated Poisson regression)	(3) # Pay (zero-inflated Poisson regression)	(4) Consumer spending (OLS)	(5) Log (consumer spending) (OLS)	(6) Return rate (GLM)
Panel A: New products						
Treatment	0.027*	0.019	0.052*	0.000052**	0.00033**	−0.092**
	(0.015)	(0.023)	(0.031)	(0.000023)	(0.00015)	(0.046)
Number of observations	132,199	132,199	132,199	132,199	132,199	20,082
Panel B: Other products						
Treatment	0.014	−0.011	0.019	0.00013	0.00045	−0.014
	(0.023)	(0.020)	(0.018)	(0.00008)	(0.00030)	(0.032)
Number of observations	132,199	132,199	132,199	132,199	132,199	17,867

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

Table 8. Effects of the AI Streaming Assistant by Streamer Popularity

	(1) # Click (zero-inflated Poisson regression)	(2) # Cart (zero-inflated Poisson regression)	(3) # Pay (zero-inflated Poisson regression)	(4) Consumer spending (OLS)	(5) Log (consumer spending) (OLS)	(6) Return rate (GLM)
Panel A: Popular streamers						
Treatment	0.026	−0.004	0.046**	0.000065**	0.0019**	−0.401***
	(0.021)	(0.022)	(0.020)	(0.000030)	(0.0009)	(0.152)
Number of observations	132,199	132,199	132,199	132,199	132,199	34,556
Panel B: Other streamers						
Treatment	−0.003	0.015	−0.002	0.00016**	0.0019	−0.092
	(0.010)	(0.021)	(0.023)	(0.00008)	(0.0013)	(0.147)
Number of observations	132,199	132,199	132,199	132,199	132,199	2,749

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

question" under its icon. The consumer can then tap its icon to start further interaction with the assistant. We consider this mode of proactive fulfillment of consumer service needs as the AI being *proactive*.

Understanding consumers' responses to *reactive* and *proactive* consumer-AI interactions provides important insights into designing AI streaming assistants for optimal service experiences in livestream selling. Empirically, we operationalize reactive interaction as consumers initiating the service by tapping the AI streaming assistant icon, and proactive interaction as the AI streaming assistant proactively offering service based on recognized consumer needs. In our study, 25.34% of consumer-AI interactions are reactive and 74.66% of interactions are proactive. We then analyze the relative effectiveness of AI's reactive and proactive interactions as well as the possible interaction effect of the two modes on consumers' purchase and product return rates.

We estimate the effects of different interaction modes between a consumer and the AI streaming assistant with the following equation:

$$\begin{aligned} &\mathit{Outcome\ Variable}_i \\ &= \beta_0 + \beta_1\,\mathit{Proactive\ Interaction}_i + \beta_2\,\mathit{Reactive\ Interaction}_i \\ &\quad + \beta_3\,\mathit{Proactive\ Interaction}_i \times \mathit{Reactive\ Interaction}_i \\ &\quad + \beta_4\,\mathit{No\ Interaction}_i + \varepsilon_i, \end{aligned} \tag{2}$$

where $\mathit{Outcome\ Variable}_i$ represents the outcomes of interest on consumer i's behavior. Further, $\mathit{Proactive\ Interaction}_i$ is a binary variable with one indicating that consumer i's comments have triggered the service from the AI streaming assistant at least once, and zero otherwise. $\mathit{Reactive\ Interaction}_i$ is a binary variable with one indicating that consumer i actively taps the AI streaming assistant at least once, and zero otherwise. The interaction term, $\mathit{Proactive\ Interaction}_i \times \mathit{Reactive\ Interaction}_i$, equals one if consumer i engages in both proactive and reactive interactions at least once, and zero otherwise. $\mathit{No\ Interaction}_i$ is a binary variable with one indicating that consumer i in the treatment group does not have any proactive or reactive interaction with the AI streaming assistant during our experiment, and zero otherwise. ε_i denotes the error term.

As presented in Table 9, the regression results show that consumers in the treatment group engaging in either proactive or reactive interactions with the AI streaming assistant exhibit increased purchase-related behaviors such as clicking on products ($p < 0.001$), adding products to shopping carts ($p < 0.001$), and purchasing products ($p < 0.001$). Meanwhile, consumers involved in AI's reactive interactions exhibit a significant reduction in product return rates ($p < 0.05$). A possible explanation is that consumers initiating the service process, with the AI streaming assistant reacting to their needs, tend to be more cautious in their purchase decisions. Additionally, the interaction term of proactive and reactive modes is significant and positive, suggesting that the two interaction modes reinforce each other in driving the outcomes. Lastly, we observe that the treatment group consumers who did not have any AI interactions, possibly reflecting a lack of engagement, are less likely than the control group to click on products ($p < 0.001$), add products to the cart ($p < 0.001$), and make purchases ($p < 0.001$) during livestream selling in our experiment.

6. Discussions

6.1. Implications for Research

To begin with, our study contributes to the literature on human-AI interaction (Huang and Rust 2018, Tong et al. 2021) by elucidating how the AI streaming assistant facilitates consumers' information acquisition and processing with a chat-based interaction in livestream selling, a context characterized by intensive, immersive, and real-time social interactions. Without the AI streaming assistant, consumers have to actively search for information across various sources and integrate that information to support their decisions. Our study is among the first work to explore how to leverage AI technologies in facilitating one-to-many, human-to-human interactions. Unlike previous findings on

Table 9. Effects of Different Consumer-AI Interaction Modes

	(1) # Click (zero-inflated Poisson regression)	(2) # Cart (zero-inflated Poisson regression)	(3) # Pay (zero-inflated Poisson regression)	(4) Consumer spending (OLS)	(5) Log (consumer spending) (OLS)	(6) Return rate (GLM)
Proactive Interaction	0.3997***	0.3398***	0.3163***	0.0034***	0.0245***	0.073
	(0.0453)	(0.0696)	(0.0607)	(0.0009)	(0.0036)	(0.145)
Reactive Interaction	0.6423***	0.4177***	0.4085***	0.0040***	0.0300***	−0.237**
	(0.0210)	(0.0322)	(0.0279)	(0.0005)	(0.0019)	(0.098)
Proactive Int. × Reactive Int.	0.4213***	0.1313*	0.2806***	0.0018**	0.0196***	−0.566***
	(0.0528)	(0.0676)	(0.0764)	(0.0008)	(0.0049)	(0.209)
No interaction	−0.1115***	−0.1022***	−0.0853***	−0.0001	−0.0019***	0.017
	(0.0105)	(0.0160)	(0.0160)	(0.0001)	(0.0004)	(0.047)
Number of observations	132,199	132,199	132,199	132,199	132,199	35,164

Notes. Proactive Int. and Reactive Int. are abbreviated forms of Proactive Interaction and Reactive Interaction, respectively. The benchmark in the regressions is consumers in the control group.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

humans' resistance to interacting with AI in the workplace (Park et al. 2021, Hornung and Smolnik 2022), we demonstrate that consumers can benefit from AI streaming assistants in livestream selling. Second, our study contributes to the literature on livestreaming, particularly on livestream selling. The extant literature on livestreaming centers on either the economic value of livestreaming (Cheng et al. 2020, Hu and Ming 2020) or how the characteristics of livestreaming influence consumer engagement and consumption (Hou et al. 2020, Zeng et al. 2020, Lu and Chen 2021, Zhao et al. 2022). Our research is among the first to examine how AI-enabled design can alleviate the streamer capacity versus consumer service demand tension in livestream selling. Although studies in the streaming context have explored AI's role in backend content production or content delivery (Menkovski and Liotta 2013, Wright et al. 2023), our research focuses on viewer-facing AI technologies in real-time interaction settings. We reveal that an AI streaming assistant complements streamers by identifying and addressing consumers' real-time needs at scale and providing intelligent information services that help consumers reduce uncertainty in making purchase decisions. Further, we extend prior research on product returns in online commerce by investigating the impact of an AI streaming assistant on product return rates in the postpurchase stage, an important yet understudied outcome in the literature (Minnema et al. 2016, Feng et al. 2024). This finding is especially important given the high return rates often associated with impulsive purchases in livestream selling.

6.2. Implications for Practice

Our study provides actionable managerial implications for managers, consumers, streamers, and sellers on livestream selling platforms. Our research evidences the efficacy of implementing an AI streaming assistant to boost sales and reduce product returns. As livestream selling platforms generally have low conversion rates during consumers' purchase journey, platform managers can consider investing in or upgrading the AI streaming assistants to provide accurate, timely, and individualized services for consumers to increase sales. Additionally, our results reveal that the implementation of the AI streaming assistant is more effective in supporting the sales of products with higher uncertainty, for example, new products that lack sales records or online reviews, and streamers with larger viewership, in which the tension between streamers' capacity constraint and consumers' service needs is more salient. In these scenarios, the AI streaming assistant plays a crucial role in promptly addressing information needs, thereby helping consumers alleviate uncertainty and facilitating decision making. Further, our results provide correlational evidence showing that AI's proactive and reactive interaction modes reinforce each other in influencing consumer behaviors; platform managers and streamers want to encourage these interactions during livestream sessions to boost consumer engagement and purchases. Meanwhile, the lower engagement observed in consumers who did not interact with the AI assistant indicates the importance of making AI interactions accessible and appealing. Platform managers can consider further refining the AI streaming assistant to enhance its accessibility, ease of use, and engagement.

6.3. Limitations and Future Research

We acknowledge that this study has several limitations, which open avenues for future research. First, our study examines the causal impacts of implementing an AI streaming assistant over a relatively short timeframe. Future research can explore the long-term implications of AI assistants in livestream selling, for example, whether and how consumers become reliant on these assistants to make purchase decisions over time. Second, the scope of our investigation is limited to the binary provision of AI streaming assistants, thereby presenting opportunities for future research to explore various capabilities and characteristics of AI technologies, such as empathy, emotional intelligence, and anthropomorphism. For example, AI assistants that exhibit empathetic interactions may build deeper emotional connections with users, possibly enhancing user trust and loyalty in the long run. Additionally, our regression analyses of consumer-AI interaction modes (reactive versus proactive) only provide correlational evidence, as the AI's interaction modes also reflect endogenous behaviors from the consumers. Thus, we urge caution in interpreting these results causally. Future work can explore how variations in consumer-AI interaction mode (i.e., proactive versus reactive) and the designs of the UI could influence the perceived level of interruption, consumer experiences, and outcomes. It is interesting for future research to build on this work and expand our understanding of AI assistants in various designs and usage scenarios. Besides, given the imaginary shopping experience of the online experiment, we are unable to directly measure how the AI assistant's provision of information affects participants' real purchases and returns (instead, we measure their purchase intention and decision-making confidence). We encourage future studies to improve realism in such experimental settings for mechanism testing. Lastly, our paper examines the effects of AI streaming assistants in the livestream selling context in which consumers are involved in intensive social interactions and are induced to make spontaneous purchase decisions. However, our empirical findings may be translated to other contexts where time-sensitive decision making occurs with limited information inputs. Future research can explore the optimal implementation of AI assistants across various contexts.

Endnotes

[1] To align with the literature on livestreaming (Lin et al. 2021), we use the term "viewers" for users in general livestreaming contexts and "consumers" for users in livestream selling contexts.

[2] Livestream selling involves streamers demonstrating and promoting products in real time through interactive video streaming, enabling instant viewer participation and product purchasing. Most streamers function as contractors for platform sellers, generally promoting products from the sellers' online stores, with sellers preselecting the products to feature in livestream sessions. Before a livestream session, the streamer configures session settings, including start time, title (topic), description, product category, cover image, and preview video (Alibaba.com 2022). Moreover, streamers pretest their equipment before the scheduled start time. When the session begins, the livestream becomes available to all platform consumers, who can find ongoing or upcoming sessions when browsing products. During sessions, streamers enthusiastically display and introduce various products to a large audience while answering questions in real time (Larson 2021, Alibaba.com 2022). Session viewers can interact with the streamer and each other by posting chat messages on the screen (Alibaba.com 2022). If consumers are interested in certain products, they can click the product links on the screen, which seamlessly transfer them to a product page.

[3] See "Asia-Pacific trends to watch for 2023: Opportunities abound in social commerce, the metaverse, and emerging markets." Accessed November 3, 2023, https://www.insiderintelligence.com/content/asia-pacific-trends-watch-2023.

[4] See "Livestream shopping survey by the influencer marketing factory." Accessed November 3, 2023, https://finance.yahoo.com/news/livestream-shopping-survey-influencer-marketing-151500745.html.

[5] To further clarify how livestream selling differs from other shopping formats, we summarize the key distinctions among livestream selling, television shopping, and conventional online commerce. As detailed in Online Appendix A, we compare them across five aspects: platform, hosts, product display, interactivity, and purchase process.

[6] See "Annual report for live stream selling in China," 36Kr Research (2020). Accessed December 4, 2023, https://pdf.dfcfw.com/pdf/H3_AP202012041436556022_1.pdf?1607092275000.pdf.

[7] Our partner platform possesses several advantages that make it an ideal research context. First, it accounts for approximately 80% of the market share in the livestream selling market in China (KPMG and AliResearch 2020), ensuring representativeness. Second, the partner platform pioneered the development of an AI streaming assistant, thereby facilitating a large-scale randomized evaluation of state-of-the-art AI technologies.

[8] The random assignment was performed in accordance with the last two digits of the consumers' account ID on the partner platform. Consumers with the last two digits of the account ID ending between 00 and 49 were assigned to the treatment group and exposed to the AI streaming assistant during the experiment. Conversely, consumers with the last two digits of the account ID ending with digits between 50 and 99 were assigned to the control group and did not have access to the AI streaming assistant in any livestream during our experiment.

[9] The platform enabled the AI streaming assistant by default for all streaming sessions in the treatment group. An extremely small proportion of streamers disabled the AI streaming assistant in their sessions in our experiment, and we excluded the related data in our analyses. Our partner platform verified that almost all streamers retained the default AI activation. Instances of streamers disabling the AI were extremely rare and negligible. The number was so small that the platform did not track or record it formally, thereby alleviating possible selection concerns.

[10] Over 10 million consumers participated in our field experiment. Because of data-sharing policies, our partner platform was only able to provide us with a randomly selected subset for analysis. To ensure sufficient statistical power, the partner platform agreed to share a random 1% sample of the consumers in the experiment, resulting in our final analysis sample of 132,199. The consumers in the sample engaged in at least one livestream session in the five-day experiment.

[11] We also report the results of mean comparisons in Table B1 in Online Appendix B. Overall, the mean comparison results align with our regression findings.

[12] $3.00\% = (e^{0.030} - 1) \times 100\%$.

[13] $10.95\% = (0.00023/0.0021) \times 100\%$.

[14] We analyze how the experimental treatment affects consumers' return rates by considering only those who have placed orders in livestream sessions during our experiment, resulting in a regression sample size of 35,164. Because purchase decisions (i.e., placing

orders) are influenced by the treatment, this may lead to an imbalance between the treatment and control groups. Therefore, before conducting regressions, we perform *t*-tests to check for significant differences between consumers who placed orders in the treatment and control groups. The *t*-test results, presented in Table C1, panel A, in Online Appendix C, indicate that we have balanced samples in both groups. Additionally, we perform the CEM one-on-one matching and replicate the regression estimations to check the robustness of our results. The balance checks of matched samples are reported in Table C1, panel B, in Online Appendix C.

[15] We calculate the effect size based on results of mean comparisons in Table B1 in Online Appendix B: $-12.55\% = (0.03511 - 0.04015)/0.04015 \times 100\%$.

[16] In Online Appendix D, we conduct a sequential logit regression to analyze how an AI streaming assistant influences the probabilities of transitions across different stages and we find consistent results suggesting that the implementation of an AI streaming assistant significantly increases the likelihood of making a purchase in the evaluation stage and decreases the probability of returning the product in the postpurchase stage.

[17] In the online experiment, given the imaginary shopping experience, direct measurement of participants' purchase and return behavior is infeasible. Thus, we measured their purchase intention and decision-making confidence using items adapted from prior literature, as these variables are highly correlated with users' actual purchase and return decisions.

[18] This online experiment received Institutional Review Board (IRB) approval. A total of 168 participants completed the online experiment. We exclude 18 participants who failed to answer the attention check question, leaving data from 150 participants for analysis.

[19] As a complement to the results in the online experiment, we also conducted consumer interviews to gather qualitative evidence in understanding how consumers internalize the AI assistant's information to support their decision-making processes. Details are reported in Online Appendix H.

[20] We also distinguish popular streamers from other streamers based on the mean value of followers that streamers had prior to the field experiment, repeat related analyses, and find consistent results.

[21] This activation triggers the assistant to present a few popular options, such as available coupons, product recommendations, and order tracking assistance, allowing for quick responses to service needs. Consumers can also engage in more personalized, conversational interactions with the assistant through text or voice.

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