The Role of AI Streamers in Live-Streaming E-Commerce: Examining the Impact of Interaction on Consumer Trust and Purchase Intention

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ABSTRACT

As AI-driven technologies become increasingly integrated into digital commerce, understanding how consumers perceive and interact with AI streamers in live shopping environments has become crucial. This study investigates how varying levels of AI streamer interactivity influence consumer trust and purchase intention, with perceived usefulness (PU) and perceived ease of use (PEU) as key mediating variables. Grounded in the Technology Acceptance Model (TAM), a controlled between-subjects experiment was conducted with 157 Chinese-speaking participants, who were randomly assigned to one of three interactivity conditions: low, medium, or high. Data were analyzed using regression analysis and mediation testing via the Model 4 of Hayes' (2022) PROCESS macro for SPSS (Version 4.2). The results showed that higher AI interactivity significantly enhanced both PU and PEU, which subsequently increased trust in the AI streamer. Further mediation analyses confirmed that PU and PEU partially mediated the relationship between AI interactivity and trust. Additionally, consumer trust strongly predicted purchase intention. These findings contribute to the growing body of literature on AI–human interaction in digital commerce and provide actionable insights for e-commerce platforms aiming to optimize AI streamer design to build consumer trust and drive purchasing behavior.

<u>KEYWORDS:</u> AI streamer, interactivity, perceived usefulness, perceived ease of use, trust, purchase intention, live commerce, mediation analysis, consumer behavior

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1. Introduction

Over the past few years, live-streaming e-commerce (LSE) has become a significant driving force in digital retail. LSE brings consumers closer to products in real time and enables streamers to play an active role in influencing consumers' shopping decisions by providing advice and product demonstrations (Shan, 2024). Historically, human (i.e., person) streamers were a major source of these live-streaming sessions. However, due to rapid developments in AI technology, numerous platforms have started employing AI streamers to increase operational efficiency and reduce labor costs. For instance, NetEase (2023) reported that JD.com employs AI streamers who never sleep, continuously operating with AI-controlled avatars that can serve consumers at any hour of the day.

Douyin, the Chinese version of TikTok, has emerged as the leading platform in the Chinese short-video and live-streaming industry, with many users engaging with the platform for e-commerce and digital marketing purposes (He et al., 2021). For example, Douyin has incorporated AI streamers extensively into its live-commerce ecosystem, sparking much discussion regarding their actual effectiveness and whether consumers truly accept them. Some scholars even predict that AI streamers will partially replace human streamers, particularly in highly cost-efficient or scalable environments (Xu & Ruan, 2023; Chen & Li, 2025). Opinions like these have been widely echoed in the media, further amplifying the conversation (Tencent News, 2023).

Despite the increasing popularity of AI streamers, key academic questions remain unresolved. Future research will continue to explore how varying degrees of AI interactivity can stimulate consumer engagement, influence purchasing decisions, and, most importantly, build consumer trust (Bai et al., 2024; Fakhimi et al., 2023). Since the majority of purchase decisions in live-streaming commerce are made on the spot, trust becomes particularly critical—it enhances the streamer's perceived credibility, and the fluidity of the streamer's performance can significantly influence buying decisions.

Building on these discussions, the purpose of the current study is to contribute to this research void by empirically investigating the effect of different amounts of AI streamer interactivity on consumer trust and purchase intention. By taking Douyin's AI streamer ecosystem as a case, this research seeks to add a timely voice to the current debate on the role and efficacy of AI in live-streaming commerce.

To provide a better understanding of this phenomenon regarding the influence of AI streamers, let us classify this group into interaction levels. Referring to the personalization model presented by Hamza (2023), this research divides AI streamers into three interactivity-level categories: low, moderate, and high interactivity. In this system, low-interactivity AI streamers are mostly used to offer simple product introductions without interacting with viewers. Some of these streamers offer simple or pre-programmed answers but never truly maintain real-time conversations, with rare exceptions. In comparison, high-interactivity AI streamers engage in real-time with the viewers' inputs, recommend videos in a personalized manner, and simulate dynamic two-way conversations. Such a taxonomy serves as the foundation for the experimental design of this study, where varied levels of interactivity are tested in terms of their effects on consumer trust and purchase intention.

Despite the popularity of AI streamers in live commerce, whether the interaction style of these AI streamers is perceived as similar to human streamers remains under question. It is still unclear whether experiences with AI streamers can generate social presence and consumer acceptance comparable to those of human streamers. It has been proposed that trust toward AI streamers might develop in a distinct way from trust toward human influencers and that AI streamers might not achieve the same level of social and persuasive effects as human-driven livestreaming (Liu & Lee, 2024). Fakhimi et al. (2023) further stated that although AI technical support for service interaction can be provided by conversational agents, these agents may demonstrate a wide personality range, yet the qualitative level of natural, social conversation remains lacking.

While many former studies have investigated the technical efficiency and business advantages of AI streamers, such as increasing user engagement, branding, and reducing labor costs (Shen & Wang, 2024), the psychological mechanisms—specifically how AI streamers garner trust in consumers—still require further exploration. Gefen et al. (2003, pp. 52–53) noted that trust is crucial for success in online commerce, and the existing evidence from AI applications does not yet make clear exactly how and when trust is built during human-agent interaction. For example, Xu et al. (2024) analyzed the role of AI streamers in improving consumer engagement in live commerce but did not focus on the impact of different types of AI interactivity on trust formation. This creates an important knowledge gap regarding psychological responses to AI streamers with varying interactive styles.

This is especially critical in the case of Douyin, which is witnessing increasing use of AI-enabled livestreaming. NetEase (2023) reported that AI streamers on Douyin are able to be massively deployed to manage workflows and sustain 24/7 broadcasting. The TikTok Corporate Report (2023) also notes that AI-powered livestreaming has become core to Douyin's e-commerce strategy in China. Given this context, the current study seeks to examine how different degrees of AI streamer interactivity influence consumer trust and purchase intention on Douyin, and it is hoped that this study can contribute to the development of empirical evidence in this growing field.

In live-streaming e-commerce, the dramatic and interactive live-room screen is a key determinant of consumers' trust in streamers. Potential viewers may trust streamers more when they believe streamers are kind, useful, and responsive (Hamza, 2023). But for AI streamers, the struggle lies in recreating natural, human conversations. As Yu et al. (2024) argued that convincing AI communicators generally fail to impress with the liveliness and variation of mood that underpin human conversation, and this fact alone reduces AI to a less credible and trustworthy entity. Therefore, understanding the effects of AI streamers' interactive behaviors on consumer trust would be significant for both theory and practice in live commerce.

This tendency can be well explained by the Technology Acceptance Model (TAM). According to TAM, individuals are likely to become skilled users of a new technology if two critical perceptions are taken into account: perceived usefulness (PU) and perceived ease of use (PEU) (Davis, 1989). In AI-supported live commerce, these constructs still play a vital role in determining the influence on consumers. Although AI streamers are distinct from human streamers, consumers would still assess whether an AI streamer is useful and communicative in the live stream. Take the AI streamer as an example: if the AI streamer can introduce products in a timely manner and interact effectively, consumers may perceive it as useful and easy to engage with, which could help to build their trust.

Furthermore, previous research also shows that consumer trust is critical in determining online purchase behavior, and in many cases serves as a mediator between consumer perceptions and purchase intentions (Hamza, 2023). Based on these considerations, the current research positions that AI streamers' interactive behaviors will affect consumers' perceived usefulness and perceived ease of use, in line with the streamlined theory of usefulness. It is these perceptions, in turn, that instill consumer trust and lead to purchase intention.

Hence, the research question addressed in this article is:

To what extent do AI streamers' interactive behaviors on Douyin enhance consumer trust, and how do PU and PEU mediate the relationship between AI interaction and consumer trust, which in turn influences purchase intention?

2. Theoretical Framework

2.1 AI Streamer Interaction and Trust.

Interactive communication is a core characteristic of live-streaming e-commerce because it fosters consumer engagement and builds trust. Cai and Wohn (2019) define live-stream shopping as "e-commerce integrated with real-time social interaction via live streams," emphasizing that such interactivity allows for immediate feedback and reduces the psychological distance between consumers and sellers. This immediacy is not just a technical advantage but a social mechanism that encourages trust. In line with this argument, Cheng (2024) asserts that "real-time, two-way communication and responsiveness provide the users with a fashionable experience, which in turn can directly influence the purchase intention."

The trust effect of interactivity in live-streaming commerce is empirically supported. Cai and Wohn (2019) found that interactive functionalities increased consumer trust. Similarly, Xu et al. (2023) argue that interactive features in livestreams serve to build trust as well as drive consumer engagement. Combined, these studies indicate that interactivity is highly important for shaping consumer perception in live-stream shopping scenarios.

Yet, in light of some recent research, the factor of trust-building in interactivity seems not reducible to technical responsiveness alone. In particular, the perceived humanness of the interaction appears to be a crucial mediator. Bai et al. (2024) reported that AI streamers offering personalized recommendations, real-time responses, and a conversational style similar to that of humans form higher social presence and enhance the interaction between consumers and AI, making consumers perceive the AI as more "human" and trustworthy. On the other hand, for AI streamers, even if interactivity is present, if the AI is mechanical and unfriendly, it is difficult for interactivity alone to build trust.

Even with these positive results, it is not clear whether AI streamers can build trust to the same extent as human streamers, especially in situations featuring high interactivity. Fakhimi et al. (2023) argue that, without naturalness or emotional richness, interactivity may not be sufficient to replicate the relational depth that human streamers offer. This continued uncertainty suggests a need for further study of how consumers think and feel about interactive AI streamers.

The power of interactivity to help build trust has been suggested to be, in part, explained by social presence theory. When the behaviors of AI streamers are made human-like (e.g., answering questions, making suggestions that correspond to users' personal preferences, and commenting in real time), AI streamers' capability to replicate the warmth, empathy, and immediacy of human interactions may further enhance their level of believability and trustworthiness (Bai et al., 2024). It remains an open question whether these artificial social signals can genuinely mimic the level of trust that people place in human streamers.

Prior research has also demonstrated that interactivity has a supportive effect on consumer trust toward live-streaming commerce (Han et al., 2024). As AI streamers' responsiveness and personalized interactions become increasingly close to real-time—mimicking those trust-building elements of back-and-forth human communication—some of these trust-enhancing effects might indeed occur even without genuine human interaction.

On this speculative basis, the present work proposes the following hypothesis:

H1: The interactivity of an AI streamer has a positive effect on consumers' trust.

2.2 The Role of Perceived Usefulness (PU) in AI Streamer Trust Formation.

The Technology Acceptance Model (TAM) has been applied in various studies to understand users' acceptance of and trust in new technologies. TAM argues that the intention to use a technology is determined by two primary perceptions, perceived usefulness (PU) and perceived ease of use (PEU), which in turn are influenced by external factors such as system design, user experience, and interaction quality (Davis, 1989; Venkatesh & Davis, 2000). Over the years, TAM has also been successfully applied beyond its original work context to online domains, such as AI services and robotic customer service interactions.

Instantaneous, high-quality browsing facilities that provide personalized, one-to-one interactive feedback for users can have a significant impact on their perception of system usefulness (Gefen & Straub, 2000). This is also the reason why TAM is especially suitable for AI streamers in live commerce, because instant product recommendations and interactions are crucial for forming consumers' purchase intentions there. In the world of live-stream shopping, trust often hinges on the consumer's confidence that the streamer can be trusted to provide useful, reliable, and relevant information. Hence, if AI streamers can provide more accurate, personalized product recommendations in real time, consumers will be more likely to feel that the stream is helpful and to trust them (Venkatesh & Davis, 2000).

For human streamers, according to previous studies, consumers trust human streamers because they provide useful product information and answer viewers' questions in a timely manner (Xu et al., 2023). But it is less clear whether the same might be true for AI streamers. Particularly, the psychological mechanism underlying the effect of AI streamers' interactive behaviors on consumers' perceived usefulness needs to be further studied.

While some recent studies have investigated consumer attitudes toward AI systems (Fakhimi et al., 2023), the effect of AI-driven interactivity on perceived usefulness in a live-stream shopping context has rarely been evaluated (Xu et al., 2024). This gap definitely deserves full attention, given that it would reflect whether and how AI streamers can establish trust with consumers through perceived usefulness, which has been widely discussed in the literature for human streamers but has been less considered for AI streamers.

Based on these findings, I propose in the current study that perceived usefulness serves as a mediator of the association between AI streamer interactivity and consumer trust. In particular, this study investigates whether increased interactivity results in enhanced perceptions of usefulness, which, in turn, enhance trust in AI streamers.

2.2.1 How AI Interactivity Enhances PU.

Perceived usefulness (PU) is the extent to which a potential user perceives that using a particular technology will bring better results or be useful in making better decisions (Davis, 1989). Regarding AI live-streaming commerce, PU specifically refers to whether consumers believe that the AI streamer's product recommendations, information delivery, and interactive behaviors are considered useful and relevant to their shopping decisions.

According to earlier lines of research, AI systems that are considered engaging and socially responsive—especially while interacting in real-time, making personalized recommendations, and adapting after user input—are more likely to lead to favorable usefulness judgments (Fakhimi et al., 2023; Hamza, 2023). This is because interactive systems can simulate real-time personal assistance, where most people tend to be more adaptable in their responses.

It is well known from empirical investigations that a high level of interactivity enhances PU by improving the system's responsiveness and practical relevance. For instance, Liu & Shrum (2002) and Teo et al. (2003) established that interactive functionalities on digital platforms significantly increase PU, as they cause the system to appear more useful and aligned with user requirements. In live-stream shopping, when the AI streamer responds in real-time, provides detailed product introductions, and offers personalized recommendations, consumers are more inclined to perceive the AI streamer as a reliable and useful shopping assistant. Consistent with this, Pai & Yeh (2014) argue that interactivity in e-commerce sites can transfer positive feelings to consumers, making them feel they better understand what to do and thereby increasing PU through web engagement.

Additionally, Le (2023) pointed out that the quality and relevance of product recommendations generated by AI are crucial factors influencing perceived usefulness in live-stream commerce. The usefulness of AI may be enhanced when users find that AI suggestions align with their personal preferences. Jamza (2023) also observed that if AI streamers carry personalized recommendation systems, they can enhance PU by providing content that closely matches the individual consumer's needs.

Taken as a whole, these results indicate that AI interactivity positively influences the perception of relevance, timeliness, and trustworthiness among consumer recommendations—factors that are most decisive in gaining consumer trust and influencing purchase decisions in live commerce.

2.2.2 PU as a Mediator Between AI Interaction and Trust.

While interactivity can moderate its positive influence on PU, PU itself also functions as an enabler to convert interactivity into consumable trust. This differs from the TAM2[1] model and trust-integrated theories, where trust is often conceptualized as a direct consequence of perceived usefulness and perceived ease of use, especially in computer-mediated environments where algorithmic agents have replaced human intermediaries (Gefen et al., 2003). In such systems, PU signifies more than just a functional assessment; it indicates the capability and reliability of the system, thereby providing a rational basis for consumer trust.

This form of trust is particularly critical in live-streaming commerce, where consumers primarily gain trust through the continuous and accurate delivery of useful and timely information related to product offerings (Ramos et al.). Prior studies have confirmed the importance of PU in fostering trust. For example, Xu et al. (2024) found that people are willing to trust AI agents that make highly beneficial product recommendations, even if such agents have low social presence. Similarly, Fakhimi et al. (2023) highlighted that frequent interaction with AI in and of itself does not lead to trust, but rather it is the extent to which the AI's responses are perceived as useful or relevant to the consumer that matters.

[1] TAM2 (Technology Acceptance Model 2) is an extension of the original TAM, adding elements like social influence and task relevance to further explain user acceptance, especially in more complex or socially interactive systems (Venkatesh & Davis, 2000).

These results advise AI streamers to save users' time, enhance decision-making efficiency, and provide individualized shopping advice, particularly when AI streamers aim to influence consumer trust (Hamza, 2023; Xu et al., 2024).

However, most previous research has focused on traditional e-commerce platforms and AI-driven customer service applications. Few studies have empirically examined the mediation of PU between AI interactivity and consumer trust in the context of live-streaming commerce. This gap is significant, as AI streamers operate in a highly dynamic, real-time shopping environment where trust-building processes may differ from traditional, static web-based interactions. To address this research gap, we put forward the following hypothesis:

H2: PU mediates the effect of AI interactivity on trust.

2.3 The Role of Perceived Ease of Use (PEU) in AI Streamer Trust Formation.

One of the main constructs in the TAM model is Perceived Ease of Use (PEU), which is the degree to which an individual believes that using a certain technology would be free of effort (Davis, 1989). Similar to PU, PEU has a significant influence on users' acceptance and trust in new technologies. Past studies have consistently shown that systems perceived as easy to use are more likely to foster user acceptance or positive attitudes toward the system, and to promote user engagement (Venkatesh & Davis, 2000).

PEU plays a relatively essential role in AI-based live-stream selling. AI streamers act as virtual shopping consultants who recommend products and assist with purchasing decisions. How well the AI streamer is able to interact clearly, instantly, and seamlessly in a practical manner significantly influences whether users find the system easy to use or difficult (Fakhimi et al., 2023). When the AI streamer is perceived as less challenging to interact with, users are more likely to experience confidence due to the ease and comfort of the interaction (Gefen et al., 2003).

However, the majority of prior PEU studies have been conducted on traditional websites or mobile applications, and the special characteristics of AI-driven, real-time shopping environments have largely been neglected (Xu et al., 2024). In contrast to static platforms, AI streamers feature on-the-fly interaction, which might bring some distinctive usability challenges. This leads to a lack of knowledge on how the interactive features of AI streamers, such as real-time responses and tailored communication, influence PEU in live commerce contexts.

To fill this gap, we are interested in whether differing degrees of AI interactivity affect PEU, and whether PEU acts as an intermediate channel that connects interactivity with the consumer trust it generates.

2.3.1 How AI Interactivity Enhances PEU.

The Technology Acceptance Model (TAM) holds that Perceived Ease of Use (PEU) reflects "the extent to which a person believes that using a particular system would be free of effort" (Davis, 1989). On the AI streamer side of things, PEU refers to the intuitiveness, slickness, and user-friendliness of the consumer experience

Related work has consistently shown that interactive system characteristics can significantly affect PEU by reducing cognitive load and providing a more intuitive user experience in the virtual world. For instance, Liu and Shrum (2002) and Teo et al. (2003) found that PEU is increased by immediate feedback and personalized attention, which help users more easily navigate online environments. Additional evidence was provided by Pai and Yeh (2014), who also demonstrated that interactive design elements could decrease users' cognitive load, enhancing overall interaction experience and usability, thus supporting our research on user interaction experiences.

As for AI-based systems, Fakhimi et al. (2023) posited that natural language processing, quick conversational responses, and adaptive interaction strategies are positively correlated with PEU. AI-powered streamers that can quickly sense user inputs (such as eye blinks and facial expressions) and react in a timely and contextually appropriate manner should be considered: (a) less cognitively challenging to use, and (b) more consumer-friendly. This aligns with the idea that interactivity—including timely responses, conversational flow, and seamless real-time adaptations—impacts PEU in the context of live commerce.

In the realm of AI streamers, the more seamless, quick, and interpretive the interaction, the more at ease consumers will feel with them. Certain features, such as immediate context-sensitive prompts (Xu et al., 2024), uninterrupted conversational flow (Fakhimi et al., 2023), and subtle interaction cues, significantly enhance perceived ease of use (Venkatesh & Bala, 2008). If AI streamers' responses are too slow, follow the script too closely, or are difficult to understand, users may find them hard to use and mentally taxing (Xu et al., 2024). Such perceptions could damage trust. Gefen et al. (2003) also found that users' frustration with an AI system can lead to distrust in the system's recommendations.

All in all, these results indicate that PEU not only alleviates cognitive effort but also builds users' confidence and trust when interacting with AI streamers. An intuitive AI streamer that provides higher-quality engagement can thus foster greater trust.

2.3.2 PEU as a Mediator Between AI Interaction and Trust.

Beyond enhancing user experience, perceived ease of use (PEU) strongly mediates trust development. According to Gefen et al. (2003), the ease-of-use factor in the TAM is determined by the extent to which users feel comfortable, assured, and confident in the reliability of the system. This theory was initially aimed at general e-commerce sites, and we can extend this inference to the domain of AI livestreaming. In this situation, intuitive and seamless interaction could contribute to reducing user uncertainty and perceived effort, thereby fostering trust in AI streamers.

This may be supported by the study of Ramos et al. (2018), who found that easy-to-use digital banking systems increased consumer trust through signaling system capability (e.g., system quality) and reducing perceived risk. Similarly, Fakhimi et al. (2023) found that trust is strongly associated with the conversational quality of an AI system: high conversational quality can increase trust in an AI interface—provided that it is usable and follows a natural interaction.

Low PEU, however, can also actively detract from trust. For example, Xu et al. (2024) pointed out that if customers encounter inaccurate answers, slow responses, or incomplete answers from AI streamers, they may begin to doubt the reliability and competence of the AI streamers. Fakhimi et al. (2023) also noted that when people struggle to use AI systems, they feel less inclined to trust the system's recommendations—even if the information provided is actually accurate. These results imply that usability is not only about comfort but is also directly linked to trust in AI-assisted environments.

Although the effect of PEU on trust has been identified in studies on e-commerce, digital banking, and AI-assisted service research (Ha & Stoel, 2009), how PEU mediates the impact of AI interactivity on trust in live-streaming commerce remains under-explored. This lack of empirical data will be addressed in this study in the form of the following research hypothesis.

H3: PEU mediates the effect of AI interactivity on trust.

Although PU and PEU are central constructs in the Technology Acceptance Model, other perspectives—such as social presence—could provide additional insights into how AI streamer interactivity influences consumer trust.

2.4 Social Presence and Trust Formation.

Social presence has been defined as the ability of a communication medium to transmit the presence of communicators as real persons and their psychological participation in a mediated interaction (Short, Williams, & Christie, 1976, p. 65). In digital contexts, greater levels of social presence are directly linked to stronger interpersonal connections, in-depth emotional engagement, and higher user trust (Gefen & Straub, 2003). Social presence refers to the extent to which consumers perceive that a system or communicator is sociable, warm, human-like, and trustworthy—even if it is only an automated system.

In relation to online purchases, it has been shown that social presence can lower the perceived psychological distance between consumers and sellers and, consequently, promote trust (Xu et al., 2024). This effect may be even stronger for interactions with AI systems, where social presence can mitigate the absence of a human interlocutor by inducing the appearance of social responsiveness and emotive engagement from the AI.

Social presence is not explicitly mentioned in the TAM, and the TAM does not include a place for it; however, it provides an additional perspective. TAM emphasizes the functional side of evaluation (perceived usefulness, ease of use) and does not extend to cover the social-emotional dimension of user interaction (Venkatesh & Davis, 2000). In AI-mediated livestreaming commerce, social presence can serve as a critical factor in shaping the effect of interactivity on consumer trust.

If the AI streamer replies quickly, asks personal questions, and replicates conversational patterns, it can substantially enhance perceived social presence. This is why the AI streamer is likely to be perceived as more human, more social, and more emotionally available to the end user. In this study, therefore, social presence is used to fill the gap of TAM in explaining how high levels of AI interactivity can increase consumer trust.

2.5 Trust and Purchase Intention in AI-driven Live Commerce.

Trust is an essential element in consumer decision-making, especially in online and live-streaming shopping events, where consumers make fast purchases through real-time endorsements (Wu et al., 2022; Han et al., 2024). In classic online shopping, consumers are often dependent on (a) peer reviews, (b) brand image, or (c) consumer-generated content to gain trust. However, in live-streaming commerce, purchase decisions rely far more on the consumer's faith in the streamer. Consumers' trust in the streamer also influences their belief in the product claim and their purchase intentions (Gefen et al., 2003).

Such a trust-purchase dynamic in human-operated live commerce platforms is well established, but little is known about how trust in AI streamers influences purchase intention. Today, there is emerging evidence that trust in AI might not lead to the same type of consumer behaviour as trust in human influencers.

For instance, parasocial relationships—one-directional emotional connections that develop between audiences (followers) and human streamers—are reported to significantly affect purchase intentions in live commerce (Sun et al., 2019). Yet, since AI streamers are less capable of building these emotional connections, is trust alone sufficient to prompt purchases in a world of AI-based shopping? AI influencers and virtual sales agents are considered to be less genuine and emotionally engaging compared to humans, and the trust-to-purchase link may therefore be weakened (Liu & Lee, 2024).

Furthermore, consumers may apply different trust criteria to AI streamers versus human streamers. Joel-Edgar et al. (2025) note that people may be more sensitive to AI-based trust errors (e.g., a product recommendation that is incorrect or suboptimal) than to trust errors from human streamers. This might suggest that AI trust violations have greater reputational implications, thereby presenting greater difficulties for AI streamers when trying to restore consumer trust following its loss.

Yet despite these differences, current evidence from the digital experience space—whether in online banking or AI-driven customer service—consistently indicates that trust is an expression of the customer's propensity to act. When users trust AI systems and perceive the AI as competent, they are more willing to accept the AI's recommendations (Xu et al., 2024).

Although AI-generated live commerce offers stronger interactivity and immediacy than traditional e-commerce, trust toward the AI streamer may also extend to purchase intentions, similar to its effect with human streamers. Therefore, we propose the following hypothesis in the present study:

H4: Consumer trust in an AI live-streamer positively influences their purchase intention.

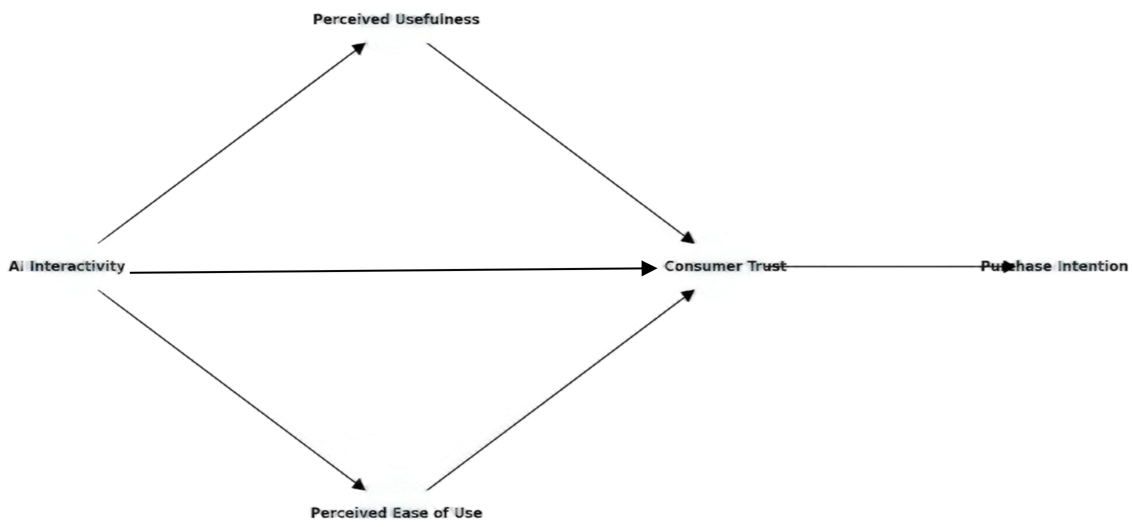


Figure 2-1. Conceptual Model Illustrating the Hypothesized Relationships Among AI Interactivity, PU, PEU, Trust, and Purchase Intention

3. Methodology

3.1 Research Design.

3.1.1 Research Method Justification.

To investigate the causal relationship of AI streamer interactivity on consumer psychological reactions and purchase intention, we employed a between-subjects design for the experiment. This method was selected because it allowed for controlled manipulation of the independent variable with minimal possibility of confounding. In particular, in a between-subjects study, potential learning effects, carryover biases, or participant fatigue that can occur when the same participants are presented with different levels of options are prevented.

The AI streamer's degree of interactivity was the primary independent variable in this study. Participants were randomly assigned to three experimental groups: low interactivity, moderate interactivity, and high interactivity. This kind of randomization serves to ensure equivalence between groups and increase internal validity.

The four dependent variables were PU, PEU, trust in AI streamer, and purchase intention. These variables were selected based on constructs from the Technology Acceptance Model (TAM) and prior studies of trust development in AI-enabled commerce. By quantifying these constructs, both consumers' cognitive appraisals and their behavioral intentions in response to different levels of AI interactivity could be fully evaluated.

3.1.2 Sampling and Participants.

I targeted participants who were native Chinese with experience engaging in AI-generated live-stream commerce on platforms like Douyin. Since the vast majority of AI livestream commerce in China is conducted in Mandarin, all participants had to be native Chinese speakers. A screening question was asked at the beginning of the survey to ensure sample relevance, requiring participants to indicate that they had seen or used AI streams in a live commerce context at least once.

In addition, only participants aged 18 years or older were eligible for inclusion. Any responses from minors were excluded during the data cleaning process to comply with ethical research standards.

A snowball sampling strategy was employed to recruit participants. Although this method has limitations in terms of generalizability, it was deemed suitable given the relatively specialized nature of AI streamer exposure. Snowball sampling allowed for the efficient identification of participants with relevant experience, which would have been challenging to achieve using probability-based sampling in this context. To maximize reach, the survey link was distributed across various personal networks, both online and offline.

The survey was administered through Qualtrics, which served solely as the digital data collection platform. Since the survey was mainly shared via the researcher's personal networks and Qualtrics is typically accessed by younger, more educated users, the resulting sample may not fully reflect the broader population. This potential sampling bias, particularly regarding age and educational background, should be carefully considered when interpreting the findings.

In total, 214 responses were initially collected. After excluding incomplete or invalid submissions, the final sample consisted of 157 valid participants. This sample size was sufficient to support the planned statistical analyses, including regression and mediation tests.

3.1.3 Stimuli and Experimental Procedure.

To investigate the causal effects of AI streamer interactivity on consumer perceptions and behavioral intentions, participants were randomly assigned to one of three experimental groups. Each group viewed a one-minute video in which an AI streamer promoted a product. All videos were identical in terms of product type, visual design, tone of voice, and delivery style. The only manipulated variable was the AI streamer's level of interactivity.

The three interactivity conditions were defined as follows:

Low Interactivity: The AI streamer presented product information in a fully scripted, monologue-style format. There were no simulated responses to viewer comments, and no audience engagement cues were included.

Medium Interactivity: The AI streamer engaged in limited interaction by providing brief, scripted responses to one or two viewer questions. These simulated responses were occasional and lacked personalization or conversational depth.

High Interactivity: The AI streamer actively and frequently engaged with viewers by addressing multiple simulated audience comments, answering real-time questions using natural language, and asking personalized follow-up questions to create a dynamic, interactive experience.

The featured product was a pack of disposable wet wipes, chosen specifically because it is a neutral, practical item with minimal emotional attachment and limited brand influence. This product selection was intended to reduce potential bias and ensure that participants focused primarily on the AI streamer's communication style rather than personal preferences or product familiarity.

Before viewing the video, participants were asked to imagine themselves participating in a typical online shopping scenario. After watching the video, they completed a questionnaire measuring their perceptions of the AI streamer and their purchase intentions.

To minimize demand characteristics and potential priming effects, participants were not informed that the study's primary focus was on the manipulation of interactivity. They were simply told that the study was designed to examine consumer responses to AI streamers in live-streaming environments.

A manipulation check was conducted to verify whether participants correctly perceived the intended interactivity levels. After watching the video, participants rated the AI streamer's perceived interactivity on a three-point scale (low, medium, high). Since the study used a between-subjects design where each participant viewed only one video, this self-reported measure served as the basis for manipulation verification. The results confirmed that participants in each group perceived significantly different levels of interactivity, indicating that the experimental manipulation was successful.

3.2 Measurement.

This study measured four core psychological constructs: Perceived Usefulness (PU), Perceived Ease of Use (PEU), Trust in the AI Streamer, and Purchase Intention (PI). All constructs were assessed using multi-item 7-point Likert scales (1 = strongly disagree, 7 = strongly agree), adapted from well-established instruments. The original scale items were carefully rephrased to reflect the AI livestream shopping context while preserving the theoretical meanings of the constructs. These adapted items were reviewed through a pilot study to ensure clarity, contextual appropriateness, and content validity.

3.2.1 Perceived Usefulness (PU).

Perceived Usefulness (PU) was measured using a three-item scale adapted from the original Technology Acceptance Model (TAM) developed by Davis (1989). While the original TAM items were designed to assess workplace technology, they were carefully rephrased in this study to fit the live-streaming e-commerce context, specifically focusing on how consumers perceive the AI streamer's usefulness in supporting product understanding and purchase decisions.

The adaptation conceptualized PU as the extent to which consumers feel the AI streamer helps them shop more efficiently and make better product choices. For example, the original item "Using this system improves my job performance" was modified to "The AI streamer helps me make better product choices during online shopping." This revision maintained the original focus on task efficiency but shifted the context from workplace productivity to consumer decision-making in a shopping environment.

The final PU measurement items were rated on a 7-point Likert scale (1 = strongly disagree, 7 = strongly agree):

The AI streamer helps me make better product choices during online shopping.

With this AI streamer's recommendation, I felt that choosing a product became more efficient.

Overall, this AI streamer was helpful for my online shopping experience.

These items specifically assessed whether the AI streamer helped participants make quicker, more confident, and better-informed purchasing decisions. Although the application context shifted from professional technology to consumer live commerce, the scale retained the core essence of PU—the perceived value and utility of using the system.

To ensure clarity and accessibility for all participants, the items were written using simple and straightforward language, minimizing potential confusion and enhancing the reliability of responses.

3.2.2 Perceived Ease of Use (PEU).

Perceived Ease of Use (PEU) was measured using a three-item scale adapted from the original Technology Acceptance Model (TAM) developed by Davis (1989). While the original TAM scale was designed to assess system usability in workplace settings, this study carefully rephrased the items to fit the AI livestream shopping environment, focusing on how easily participants could engage with the AI streamer.

For example, the original item "This system is easy to use" was revised to "Interacting with this AI streamer was easy to follow." This modification maintained the core measurement of ease of use while aligning the wording with the consumer livestream context. Additionally, care was taken to avoid double-barreled items by ensuring that each statement measured a single, clearly defined dimension.

Another example of the adaptation focused on participants' subjective experience: "Overall, engaging with this AI streamer during the livestream felt relaxed and effortless."

This item emphasizes the natural flow and ease of the interaction, without suggesting system complexity or technical operation.

The final PEU measurement items were rated on a 7-point Likert scale (1 = strongly disagree, 7 = strongly agree):

It was easy for me to understand how to watch and engage with this AI streamer's livestream.

Interacting with this AI streamer was easy to follow.

Overall, engaging with this AI streamer during the livestream felt relaxed and effortless.

These adapted items specifically captured whether participants perceived the AI streamer as easy to understand, easy to interact with, and effortless to follow. Although the wording was adjusted for the livestream shopping scenario, the items retained the core meaning of PEU—how simple, intuitive, and cognitively stress-free the interaction feels.

The questions were written in simple and accessible language to ensure all participants could clearly understand the statements and respond accurately based on their actual interaction experience.

3.2.3 Trust in the AI Streamer.

To measure consumer trust in the AI streamer, this study adapted items from Gefen et al. (2003), who originally developed a trust scale for online shopping contexts. In their work, trust focused on the credibility of online sellers and the security of transactions. However, the present study shifts this focus to trust in the AI streamer as a communication agent, rather than trust in the website or payment systems.

Therefore, the item wording was carefully adjusted to align with the livestream shopping environment, where trust is based on the AI streamer's product presentation and communication style. For example, the original item "I believe the online seller is honest" was revised to "I trust that this AI streamer is honest when introducing products and does not exaggerate." Additionally, items related to transaction security were excluded because the study does not investigate system-level trust or financial processes, but specifically focuses on the perceived honesty, reliability, and communication integrity of the AI streamer.

The final trust scale included the following items, measured on a 7-point Likert scale (1 = strongly disagree, 7 = strongly agree):

I believe this AI streamer is trustworthy.

I trust that this AI streamer is honest when introducing products and does not exaggerate.

I find the product information provided by this AI streamer to be reliable and not misleading.

Overall, I am willing to rely on this AI streamer's recommendations to assist my decision-making.

These items specifically assess whether users perceive the AI streamer as honest, credible, and reliable in providing product information. The design intentionally focuses on the trustworthiness of the AI's communication rather than its technical functionality or purchasing processes. This approach fits the livestream shopping context, where trust is largely built through direct interaction and verbal communication.

Additionally, the trust items were carefully constructed to avoid overlapping with purchase intention measures. By focusing purely on information reliability and recommendation credibility, the scale ensures that trust and purchase intention are treated as distinct psychological constructs, avoiding potential measurement contamination.

3.2.4 Purchase Intention (PI).

To measure purchase intention, this study adapted items from Spears and Singh (2004), who define purchase intention as a person's expressed likelihood or plan to buy a product in the future. Their original scale is widely validated and frequently applied in consumer behavior research, typically using straightforward statements such as "I intend to buy this product."

In the present study, the core structure of the original items was retained, but the wording was adjusted to explicitly link purchase intention to the AI streamer's recommendation in the livestream scenario. This ensures that participants' responses reflect their intention to purchase based specifically on the AI streamer's influence, rather than on general product preferences.

The final purchase intention scale included the following items, measured on a 7-point Likert scale (1 = strongly disagree, 7 = strongly agree):

After hearing this AI streamer's introduction, I am considering purchasing the product.

I am likely to purchase the product recommended by this AI streamer.

In the future, I plan to buy products based on this AI streamer's recommendations.

If I get the chance, I am willing to try other products introduced by this AI streamer during livestreams.

These items capture both the immediate purchase intention and the participant's long-term openness to the AI streamer's future recommendations. By framing purchase intention within the livestream context, the scale more accurately reflects the study's goal: to assess how the AI streamer's communication influences consumer decision-making.

After watching the given live video, participants were asked to indicate to what extent they believed the AI streamer was interactive. This was used as a manipulation check to test whether the experimental conditions were actually perceived as intended.

All survey items (including the manipulation check) were translated into Chinese via a back-translation procedure to ensure language equivalence and cultural sensitivity. The method entailed a forward translation from English to Chinese by a bilingual translator, followed by a separate back translation into English. The two English versions were compared and harmonized to achieve semantic equivalence and cultural relevance for native Chinese speakers.

3.2.5 Behavioral and Demographic Variables.

The survey also included demographic and behavioral variables not used in the present article to allow for a fuller characterization of the participants and to control for possible differences among consumers in their experiences with livestream shopping. In particular, participants provided their age, gender, educational level, and the frequency of watching livestreams.

Participants' age was reported in years as a continuous response. (Participants under 18 were automatically redirected to the end of the survey.)

Gender was collected through a categorical response to the options: "Male," "Female," and "Other / Do not want to say."

Education was categorized using a standardized order of educational levels, ranging from high school to postgraduate.

The collection of these demographics was used to describe the general characteristics of the sample and served as background information for determining how user profiles could affect consumer responses.

The frequency of livestream use was also assessed on a 5-point Likert scale (1 = never/nothing, 5 = very often/a lot). This item aimed to reflect the extent to which participants engaged in livestream shopping overall, regardless of whether it involved human or AI hosts. By examining this behavioral variable, the study was able to control for participants' baseline familiarity and previous exposure to livestream commerce.

These demographic and behavioral characteristics served a dual role: They provided important reference points for describing the sample. They served as covariates in additional statistical tests, enabling us to statistically interpret the observed influence of AI streamer interactivity on participant beliefs in the context of individual differences.

These further indicators were included to enhance the validity and generalizability of the results.

3.3 Manipulation Check and Pilot.

To test whether the interactivity manipulation was successful, we included a manipulation check with a single-item measure in the pilot study. Based on the recommended and/or previewed model for the experiment (causal and progressive), participants were asked to indicate to what extent (low, medium, or high) they believed the AI streamer in the provided livestream video would interact. This check allowed us to determine whether participants correctly identified the intended level of interactivity in the three experimental conditions.

In the pilot study ($N = 30$), perceived interactivity was measured using a 3-point Likert scale (1 = low, 2 = medium, 3 = high). The results showed a clear, stepwise increase in perceived interactivity across the conditions. Specifically, the low interactivity group reported a mean score of $M = 1.45$, $SD = 0.69$, the medium interactivity group reported $M = 1.80$, $SD = 0.42$, and the high interactivity group reported $M = 2.22$, $SD = 0.67$.

Although no formal statistical tests were conducted due to the limited pilot sample size, the consistent directional trend in the mean scores indicates that participants generally perceived the intended distinctions among the three levels of interactivity. Based on these pilot insights, the high-interactivity script was further refined to make the differences between conditions even more distinct and easily recognizable.

In the low interactivity condition, the AI streamer provided only basic, scripted product information, using highly repetitive phrases such as "This product is very useful" and "You can use it for daily cleaning." The AI streamer did not respond to any viewer comments, nor did it engage in any conversational behavior. The communication remained strictly one-way, focusing entirely on product description without interaction.

In the medium interactivity condition, the AI streamer demonstrated occasional engagement by briefly answering simulated viewer questions. For example, when a viewer asked, "Does this product come in other sizes?" the AI streamer responded with "Yes, different sizes are available." The responses were minimal, scripted, and limited in both frequency and depth. There were no personalized suggestions or proactive audience engagement.

In the high interactivity condition, the AI streamer actively and frequently engaged with viewers in a dynamic, conversational style. The streamer initiated interaction with comments like "Hi there! I see you're watching—feel free to ask me anything!" and followed up with rhetorical questions such as "Would you like to see more products like this?" Additionally, the AI streamer provided personalized suggestions using statements like "I think you might like this one—it's very popular today." The overall interaction simulated a natural, responsive, and socially rich conversation.

The pilot study established that the participants were able to correctly and consistently perceive the intended differences in AI interactivity among the three conditions. This ensures the internal validity of the experimental manipulation and provides a solid foundation for interpreting the causal effects of interactivity in the main study.

3.4 Validity Testing: Exploratory Factor Analysis.

To explore the convergent and discriminant validity of the constructs used in the analysis (PU, PEU, Trust, and Purchase Intention), we conducted an exploratory factor analysis (EFA) (Kaiser, 1974), using principal axis factoring for each construct separately. The Kaiser-Meyer-Olkin (KMO) measure and Bartlett's Test of Sphericity were used to ensure that the sample size was adequate and that factor analysis was appropriate for factor extraction.

Firstly, to explore the underlying structure of the perceived usefulness (PU) items, a Principal Axis Factoring (PAF) was conducted using direct oblimin rotation based on eigenvalues greater than 1.00. The Kaiser-Meyer-Olkin (KMO) measure verified the sampling adequacy for the analysis, with a KMO value of .737, which exceeds the acceptable minimum of .60 (Kaiser, 1974). Bartlett's Test of Sphericity was significant, $\chi^2(3) = 231.36$, $p < .001$, indicating that the correlations between items were sufficiently large for factor analysis (Bartlett, 1954). The scree plot and eigenvalue analysis supported a one-factor solution, with the first factor eigenvalue close to 2.5. All three items loaded onto this factor, with loadings ranging from .273 to .396, suggesting moderate but acceptable item contributions (see Table 3-1). These results indicate that PU can be considered a reliable and valid unidimensional construct.

Secondly, to explore the underlying structure of the perceived ease of use (PEU) items, a Principal Axis Factoring (PAF) was performed using direct oblimin rotation based on eigenvalues greater than 1.00. The Kaiser-Meyer-Olkin (KMO) measure verified the sampling adequacy for the analysis, with a KMO value of .683, which exceeds the minimum threshold of .60 (Kaiser, 1974). Bartlett's Test of Sphericity was significant, $\chi^2(3) = 118.21$, $p < .001$, indicating that the correlation matrix was appropriate for factor analysis (Bartlett, 1954). The scree plot and eigenvalue analysis supported a one-factor solution, with the first factor eigenvalue exceeding 2.0. Factor loadings ranged from .229 to .489 across the three items, suggesting that the items adequately measured the underlying construct (see Table 3-1). These results support the conclusion that PEU is a reliable and valid unidimensional construct.

Thirdly, to explore the underlying structure of the trust items, a Principal Axis Factoring (PAF) was conducted using direct oblimin rotation based on eigenvalues greater than 1.00. The Kaiser-Meyer-Olkin (KMO) value of .827 indicated meritorious sampling adequacy (Kaiser, 1974). Bartlett's Test of Sphericity was significant, $\chi^2(6) = 334.21$, $p < .001$, confirming that the correlation matrix was suitable for factor analysis (Bartlett, 1954). The scree plot and eigenvalue analysis indicated a one-factor solution, with the first factor eigenvalue close to 3.0. Factor loadings for the four items ranged from .210 to .386, indicating acceptable contributions to the underlying construct (see Table 3-1). These results support the reliability and unidimensionality of the trust construct.

Finally, to explore the underlying structure of the he purchase intention items, a Principal Axis Factoring (PAF) was performed using direct oblimin rotation based on eigenvalues greater than 1.00. The Kaiser-Meyer-Olkin (KMO) measure was .852, indicating meritorious sampling adequacy (Kaiser, 1974). Bartlett's Test of Sphericity was significant, $\chi^2(6) = 430.44$, $p < .001$, suggesting that the items were sufficiently intercorrelated for factor analysis (Bartlett, 1954). The scree plot and eigenvalue analysis supported a one-factor solution, with the first factor eigenvalue exceeding 3.0. Factor loadings ranged from .181 to .348 across the four items, suggesting satisfactory measurement of the underlying construct (see Table 3-1). These findings confirm that purchase intention can be treated as a reliable and valid unidimensional construct.

For all four constructs, the factor analyses, scree plots, and the KMO/Bartlett tests indicated that the latent factors were validly assessed as uni-dimensional constructs. These findings partially validated the rationale for using combined means of each construct in subsequent regression and mediation tests.

3.5 Reliability Analysis.

Cronbach's alpha coefficient was employed to test the reliability of the survey. A Cronbach's alpha value of .70 is frequently considered satisfactory, and values above .80 are regarded as reflecting good to excellent reliability (Hair et al., 2019).

The Perceived Usefulness (PU) scale, measured with three items, yielded a Cronbach's alpha of .86, indicating excellent internal consistency. This suggests that the items consistently captured participants' perceptions of how useful the AI streamer's product recommendations were.

The Perceived Ease of Use (PEU) scale, also consisting of three items, achieved a Cronbach's alpha of .76. This value reflects acceptable internal consistency, indicating that the items reliably measured participants' perceptions of the AI streamer's user-friendliness and ease of interaction.

The Trust construct, measured with four items, demonstrated strong reliability with a Cronbach's alpha of .88. This result indicates that participants consistently assessed the AI streamer's honesty, reliability, and trustworthiness across items.

The Purchase Intention scale, which included four items, achieved the highest reliability with a Cronbach's alpha of .91, demonstrating excellent internal consistency. This finding confirms that the scale effectively captured participants' likelihood to purchase products recommended by the AI streamer.

Collectively, these results provide strong evidence that all four multi-item scales used in this study exhibit good to excellent internal consistency and are reliable measures for further statistical analyses (see Table 3-1).

Table 3-1. Factor Loadings, Internal Consistency (Cronbach's α) for the Four Constructs Measured in the Study.

Items	Perceived Usefulness (PU)	Perceived Ease of Use (PEU)	Trust	Purchase Intention
PU1	.27			
PU2	.38			
PU3	.40			

PEU1		.23		
PEU2		.49		
PEU3		.34		
Trust1			.21	
Trust2			.23	
Trust3			.39	
Trust4			.26	
PI1				.18
PI2				.30
PI3				.35
PI4				.24
Cronbach's α	.86	.76	.88	.91

4. Results

4.1 Descriptive Statistics and Sample Characteristics.

This study specifically targeted native Chinese speakers to align with the linguistic and cultural environment in which AI-driven live-streaming commerce is most actively used. Given that the majority of AI streamers in China operate in Mandarin-language platforms such as Douyin, recruiting participants who are native Chinese speakers ensured both contextual relevance and ecological validity. Participants were recruited online using a combination of social media platforms and community forums, where the survey link and study invitation were openly distributed. This approach enabled access to a diverse but digitally active consumer group with prior exposure to live-streaming commerce. A total of 214 responses were initially collected. Following rigorous data cleaning procedures—such as excluding incomplete surveys, inconsistent responses, and participants who failed attention-check questions—157 valid cases remained for the final analysis. This sample size was sufficient to meet the statistical requirements for the planned analyses, including regression and mediation tests. By focusing on this specific participant group, the study ensures that the findings are both demographically appropriate and practically relevant to the Mandarin-speaking live-stream shopping environment where AI streamers are currently deployed.

4.1.1 Demographics and Livestreaming Habits.

The final sample had an average age of 26.67 years (SD = 5.77), with ages ranging from 18 to 100. Some participants who reported being under 12 years old were automatically excluded during the survey process through a pre-set skip logic to ensure ethical compliance. The age distribution was positively skewed toward younger adults, with 68.6% of participants aged between 18 and 30. This demographic concentration aligns with the primary user base of livestream e-commerce platforms in China, which typically attract younger consumers.

Regarding livestream viewing habits, participants generally reported moderate to high levels of engagement. Specifically, 42.4% indicated that they "occasionally" watch livestreams (1 – 2 times per month), while 21.5% reported "frequent" viewing (1 – 2 times per week) and 26.6% reported "very frequent" viewing (3 times or more per week). Only 9.5% indicated they "never" watch livestreams. On a 5-point scale, the mean viewing frequency score was 4.46 (SD = 1.39), indicating that most participants had substantial prior exposure to livestream shopping.

In terms of average viewing duration per session, the majority of participants (72.4%) tended to watch for less than 30 minutes at a time. Specifically, 30.1% reported watching for less than 10 minutes per session, and 42.3% watched for 10 to 30 minutes. A smaller proportion of participants engaged in longer viewing sessions: 21.8% reported watching for 30 to 60 minutes, and only 5.8% watched for more than one hour per session. The mean session length was 3.43 (SD = 1.69) on a 5-point scale, suggesting that most participants experienced livestream shopping as a short and casual activity rather than an extended engagement.

Participants' self-reported purchase tendency through livestreams exhibited considerable variability. The average purchase tendency score was 41.22 (SD = 22.60), with a broad range from 3 to 100. This wide distribution suggests that although some participants were highly inclined to make livestream purchases, others primarily engaged as passive viewers. This heterogeneity reflects meaningful individual differences in consumer behavior, even within a sample that was relatively young and livestream-aware.

Taken together, these descriptive findings provide a detailed demographic and behavioral profile of the sample: a predominantly young user group, generally engaged in livestream commerce, but with varying levels of purchase involvement. These characteristics establish a strong contextual basis for the subsequent inferential analyses examining how AI streamer interactivity impacts consumer trust and purchase intention.

4.1.2 Gender Distribution.

Among the 159 valid responses, 59.1% of participants were female (n = 94) and 37.7% were male (n = 60). A small proportion of participants identified as "other" (1.9%, n = 3), and 1.3% (n = 2) preferred not to disclose their gender. This female-majority sample aligns with observed patterns in livestream shopping, where women are often more active participants (Xu et al., 2023). The gender distribution should be taken into consideration when interpreting the results, as it may reflect gendered differences in engagement with livestream commerce and perceptions of AI streamers.

4.1.3 Education Level.

The sample exhibited a relatively high level of educational attainment. Specifically, 44.6% (n = 70) held a bachelor's degree, and 35.7% (n = 56) had completed a master's degree or higher. Additionally, 12.7% (n = 20) reported having an associate degree (大专), while 7.0% (n = 11) indicated a high school education or below. Only two participants did not answer this item.

This skew toward higher educational backgrounds may influence the cognitive processing of digital technologies, including AI-driven livestreams. Prior research suggests that more educated consumers often possess greater technological literacy and may critically evaluate AI interactions more rigorously (Venkatesh et al., 2003). This characteristic of the sample should be considered when generalizing the study's findings to broader consumer populations.

4.1.4 Previous Exposure to AI Streamers.

Participants were equally divided on whether they had watched AI-hosted livestreams in the past. Exactly 50% ($n = 78$) reported that they had seen an AI streamer before, while the other 50% had not. This even balance is especially valuable for the current experiment because it enables meaningful comparisons to be made between participants with and without prior exposure.

Furthermore, this segmentation offers the opportunity to investigate whether familiarity with AI streamers moderates the relationship between consumers' perceptions of interactivity with, trust in, and purchase intention toward AI streamers. Understanding whether previous experience affects psychological reactions to AI streamers may provide practical insights for e-commerce platforms that cater to livestream audiences with varying levels of experience with AI streamers.

4.1.5 Summary of Sample Characteristics.

The general demographics of this sample reflect young and well-educated individuals who were slightly female-dominant and equally split in terms of prior exposure to AI streamers. These attributes provide an important backdrop for the study's results, as users' age, education, and familiarity with AI livestreaming may influence consumers' perceptions of interactivity, trust, and purchase behavior.

4.1.6 Descriptive Analysis of Core Variables.

Descriptive statistics were used to provide a preliminary view of participants' responses to the four crucial psychological constructs (PU, PEU, Trust, and Purchase Intention), which were analyzed prior to testing the proposed hypotheses. All constructs were measured using 7-point Likert scales (1 = strongly disagree; 7 = strongly agree).

The mean score for Perceived Ease of Use (PEU) was 4.16 ($SD = 1.32$), suggesting that participants generally found the AI streamer easy to interact with. Perceived Usefulness (PU) had a mean score of 3.81 ($SD = 1.47$), indicating moderate agreement that the AI streamer was helpful in supporting product selection and shopping decisions.

The average rating for Trust in the AI streamer was 3.79 (SD = 1.43), reflecting a neutral to moderately positive perception of the AI streamer's credibility and reliability. Purchase Intention was slightly lower, with a mean score of 3.39 (SD = 1.54), suggesting that while some participants were inclined to act on the AI streamer's recommendations, many remained cautious or undecided about making a purchase.

These descriptive tendencies provide initial indications of participants' cognitions and feelings towards AI streamers. More concretely, the sample was relatively positive with respect to cognitive perceptions about the usability, perceived helpfulness, and trustworthiness of the AI streamer, and moderate with respect to their behavioral intentions to purchase.

All four variables demonstrated sufficient variability across the 7-point scale to justify conducting follow-up regression and mediation analyses. Although normality tests had not been formally performed, an inspection of the distribution curves suggested they were roughly symmetric, indicating the adequacy of using parametric methods in this analysis.

4.2 Results.

This section presents the findings from statistical analyses used to test the proposed hypotheses. Linear regression and mediation models were used to investigate the associations between AI interactivity, PEU, trust in the AI streamer, and users' purchase intention. All statistical analyses were conducted in SPSS 28.0.

4.2.1 Hypothesis 1: The interactivity of an AI streamer positively affects consumers' trust.

To test Hypothesis 1, which proposed that increasing the interactivity of an AI streamer would enhance consumers' trust, a one-way analysis of variance (ANOVA) was conducted. The independent variable was AI interactivity, categorized into three levels (low, medium, and high), and the dependent variable was users' trust in the AI streamer.

To test whether AI streamer interactivity influences consumer trust, a one-way ANOVA was conducted. The analysis revealed a significant main effect of AI interactivity on trust, $F(2, 154) = 45.63$, $p < .001$, partial $\eta^2 = .37$. This indicates that trust levels significantly differed across the low, medium, and high interactivity groups. The effect size was large, suggesting that approximately 37% of the variance in trust could be explained by the AI streamer's level of interactivity.

Descriptive statistics showed that participants in the low-interactivity condition reported lower trust scores (M = 2.74, SD = 0.98) than those in the medium-interactivity condition ($M = 3.75$, $SD = 0.95$) and the high-interactivity condition ($M = 4.88$, $SD = 1.44$). Bonferroni post hoc comparisons revealed that participants in the medium-interactivity condition scored significantly higher in trust ($M = 3.75$, $SD = 0.95$) than those in the low-interactivity condition ($M = 2.74$, $SD = 0.98$), $p < .001$. Participants in the high-interactivity condition scored significantly higher in trust ($M = 4.88$, $SD = 1.44$) than both the medium-interactivity group ($p < .001$) and the low-interactivity group ($p < .001$). All pairwise comparisons were significant at the .05 level.

In sum, the results strongly support Hypothesis 1. Participants reported significantly higher levels of trust in the AI streamer as its interactivity increased from low to medium and from medium to high. These findings underscore the importance of designing AI streamers with stronger interactive capabilities to foster greater user trust in livestream shopping contexts.

4.2.2 Hypothesis 2: Perceived Usefulness (PU) as a Mediator.

To test Hypothesis 2, a mediation analysis was conducted using Model 4 of Hayes' (2022) PROCESS macro in SPSS. The independent variable was AI interactivity, dummy-coded with the low-interactivity condition as the reference group. Perceived usefulness (PU) was included as the mediator, and trust in the AI streamer was the outcome variable. The analysis used 5,000 bootstrap samples with 95% bias-corrected confidence intervals.

The total effect model showed that AI interactivity significantly predicted trust. Compared to the low-interactivity group, the medium-interactivity condition significantly increased trust ($B = 1.01$, $SE = 0.22$, $t = 4.55$, $p < .001$, 95% CI [0.57, 1.45], $\beta = .71$). The high-interactivity condition showed an even stronger effect ($B = 2.14$, $SE = 0.22$, $t = 9.55$, $p < .001$, 95% CI [1.70, 2.58], $\beta = 1.49$).

AI interactivity also significantly predicted perceived usefulness. For the medium-interactivity group, $B = 1.25$, $SE = 0.20$, $t = 6.33$, $p < .001$, 95% CI [0.86, 1.64], $\beta = .84$. For the high-interactivity group, $B = 2.65$, $SE = 0.20$, $t = 13.38$, $p < .001$, 95% CI [2.26, 3.05], $\beta = 1.80$.

In the mediation model, PU significantly predicted trust ($B = 0.88$, $SE = 0.06$, $t = 15.45$, $p < .001$, 95% CI [0.77, 0.99], $\beta = .91$). After controlling for PU, the direct effects of interactivity on trust became non-significant. For the medium-interactivity group, $B = -0.09$, $SE = 0.16$, $t = -0.55$, $p = .58$, 95% CI [−0.40, 0.22], $\beta = -.06$. For the high-interactivity group, B = −0.20, SE = 0.21, t = −0.98, p = .33, 95% CI [−0.61, 0.21], β = −.14.

Bootstrapping confirmed significant indirect effects. For the medium-interactivity group, the indirect effect was B = 1.10, BootSE = 0.15, 95% CI [0.81, 1.40], partially standardized β = .77. For the high-interactivity group, the indirect effect was B = 2.34, BootSE = 0.23, 95% CI [1.90, 2.82], partially standardized β = 1.63. Since zero was not included in either confidence interval, the results support a full mediation. These findings suggest that perceived usefulness fully explains the effect of AI interactivity on users' trust. The detailed mediation results for perceived usefulness (PU) as a mediator between AI interactivity and trust are summarized in Table X.

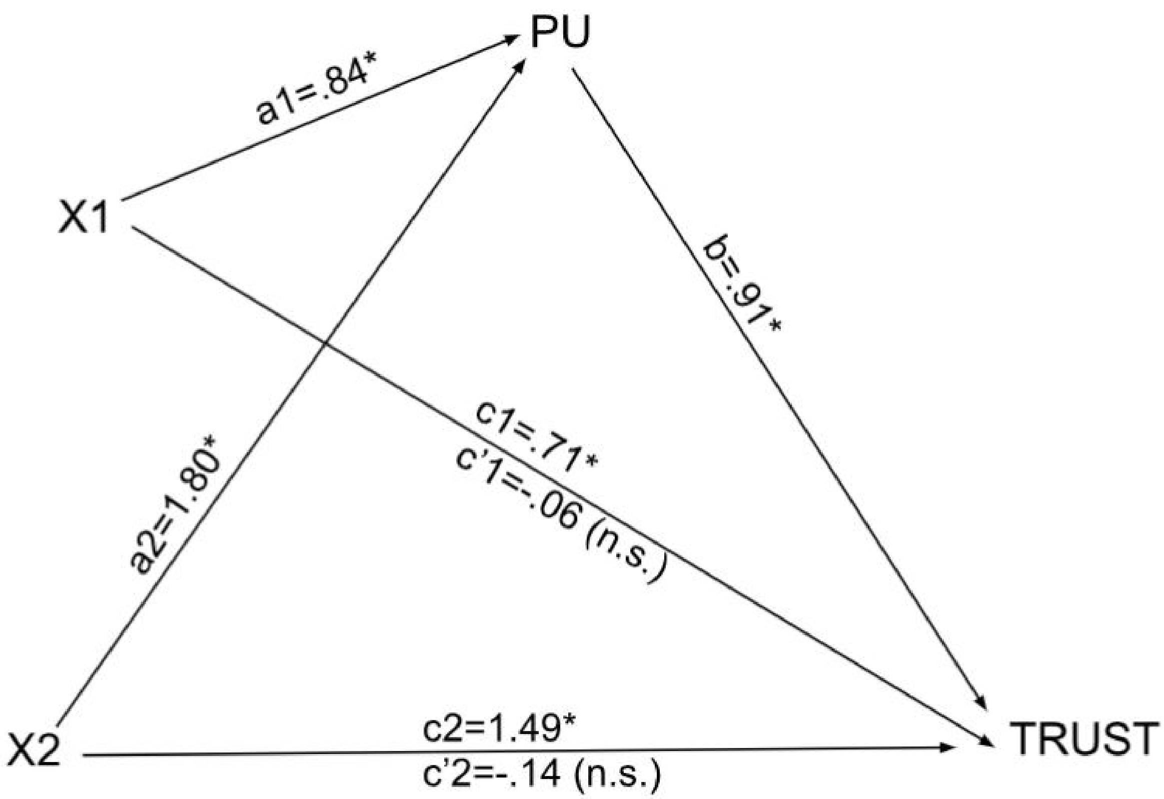
Table 4-1. Mediation analysis results for PU as a mediator between AI interactivity and trust.

Path	**B**	**SE**	**t**	**p**	**95% CI [LL, UL]**	**β**
X → Trust (Total Effects)						
Medium vs. Low (X_1)	1.01	0.22	4.55	< .001	[0.57, 1.45]	0.71
High vs. Low (X_2)	2.14	0.22	9.55	< .001	[1.70, 2.58]	1.49
X → PU						
Medium vs. Low (X_1 → PU)	1.25	0.20	6.33	< .001	[0.86, 1.64]	0.84
High vs. Low (X_2 → PU)	2.65	0.20	13.38	< .001	[2.26, 3.05]	1.80
PU → Trust	0.88	0.06	15.45	< .001	[0.77, 0.99]	0.91
X → Trust (Direct Effects)						
Medium vs. Low (X_1 → Trust)	-0.09	0.16	-0.55	.58	[-0.40, 0.22]	-0.06
High vs. Low (X_2 → Trust)	-0.20	0.21	-0.98	.33	[-0.61, 0.21]	-0.14
Indirect Effects (Bootstrapped)						
X_1 → PU → Trust	1.10	0.15	—	—	[0.81, 1.40]	0.77

$X_2 \rightarrow$ PU $\rightarrow$ Trust	2.34	0.23	—	—	[1.90, 2.82]	1.63

Note. X refers to the level of AI interactivity with the low-interactivity group as reference. β = Standardized beta coefficients. CI = Confidence Interval.

As illustrated in Figure 4-1, perceived usefulness fully mediated the relationship between AI interactivity and user trust in the AI streamer.



Note. All coefficients represent standardized β values. X_1 = medium vs. low interactivity; X_2 = high vs. low interactivity. PU = Perceived Usefulness. TRUST = Trust in AI streamer.

*p < .05. (n.s.) = not significant.

Figure 4-1. Mediation model showing the effect of AI interactivity on trust via perceived usefulness (PU).

4.2.3 Hypothesis 3: Perceived Ease of Use (PEU) as a Mediator.

To test Hypothesis 3, a mediation analysis was conducted using Model 4 of Hayes' (2022) PROCESS macro in SPSS. The independent variable was AI interactivity, dummy-coded with low interactivity as the reference group, perceived ease of use (PEU) as the mediator, and trust as the dependent variable. Bootstrapping with 5,000 resamples and 95% confidence intervals was used.

The total effect model showed a significant positive effect of AI interactivity on trust. Compared to the low-interactivity group, participants in the medium-interactivity condition reported significantly higher trust ($B = 1.01$, $SE = 0.22$, $t = 4.55$, $p < .001$, 95% CI [0.57, 1.45], $\beta = 0.71$). Similarly, the high-interactivity condition also showed significantly greater trust compared to the low-interactivity group ($B = 2.14$, $SE = 0.22$, $t = 9.55$, $p < .001$, 95% CI [1.70, 2.58], $\beta = 1.49$).

Next, AI interactivity significantly predicted perceived ease of use (PEU). The medium-interactivity condition significantly enhanced participants' perceived ease of use compared to the low-interactivity group ($B = 1.07$, $SE = 0.19$, $t = 5.70$, $p < .001$, 95% CI [0.70, 1.44], $\beta = 0.80$). The effect was even stronger in the high-interactivity group ($B = 2.26$, $SE = 0.19$, $t = 11.99$, $p < .001$, 95% CI [1.89, 2.63], $\beta = 1.70$), confirming that greater interactivity led participants to perceive the AI streamer as easier to use.

When including PEU in the mediation model, perceived ease of use significantly predicted trust ($B = 0.61$, $SE = 0.08$, $t = 7.37$, $p < .001$, 95% CI [0.45, 0.77], $\beta = 0.56$). After controlling for PEU, the direct effect of medium interactivity on trust became non-significant ($B = 0.36$, $SE = 0.21$, $t = 1.72$, $p = .09$, 95% CI [-0.05, 0.78], $\beta = 0.25$), while the direct effect of high interactivity remained significant, though reduced ($B = 0.76$, $SE = 0.27$, $t = 2.85$, $p = .01$, 95% CI [0.23, 1.29], $\beta = 0.53$). This indicates that PEU partially mediates the relationship between AI interactivity and trust, with direct effects still present at higher interactivity levels.

Bootstrapping analyses confirmed significant indirect effects through PEU. For medium interactivity, the indirect effect was significant ($B = 0.65$, $BootSE = 0.13$, 95% CI [0.38, 0.91], partially standardized $\beta = 0.45$). Similarly, for high interactivity, the indirect effect was significant as well ($B = 1.38$, $BootSE = 0.23$, 95% CI [0.88, 1.79], partially standardized $\beta = 0.96$). Because the confidence intervals did not include zero, these mediation effects were statistically reliable.

In summary, Hypothesis 3 received partial support. While perceived ease of use significantly mediated the relationship between AI interactivity and trust, this mediation was partial—particularly for the high-interactivity condition, where direct effects remained significant. This suggests that although perceived ease of use plays a crucial role, other mechanisms might also contribute to how interactivity builds trust in AI streamers. Table 4-2 summarizes the mediation analysis results, highlighting the direct and indirect effects of perceived ease of use (PEU) on the relationship between AI interactivity and trust.

Table 4-2. Mediation Analysis Results for Perceived Ease of Use (PEU) between AI Interactivity and Trust

Path	B	SE	t	p	95% CI [LL, UL]	β
X → Trust (Total Effects)						
Medium vs. Low (X1)	1.01	0.22	4.55	< .001	[0.57, 1.45]	0.71
High vs. Low (X2)	2.14	0.22	9.55	< .001	[1.70, 2.58]	1.49
X → PEU						
Medium vs. Low (X1)	1.07	0.19	5.70	< .001	[0.70, 1.44]	0.80
High vs. Low (X2)	2.26	0.19	11.99	< .001	[1.89, 2.63]	1.70
PEU → Trust	0.61	0.08	7.37	< .001	[0.45, 0.77]	0.56
X → Trust (Direct Effects)						
Medium vs. Low (X1)	0.36	0.21	1.72	.09	[-0.05, 0.78]	0.25
High vs. Low (X2)	0.76	0.27	2.85	.01	[0.23, 1.29]	0.53

Note. X refers to the level of AI interactivity with the low-interactivity group as reference. β = Standardized beta coefficients. CI = Confidence Interval.

As illustrated in Figure 4-2, Perceived Ease of Use partially mediated the relationship between AI interactivity and user trust in the AI streamer.

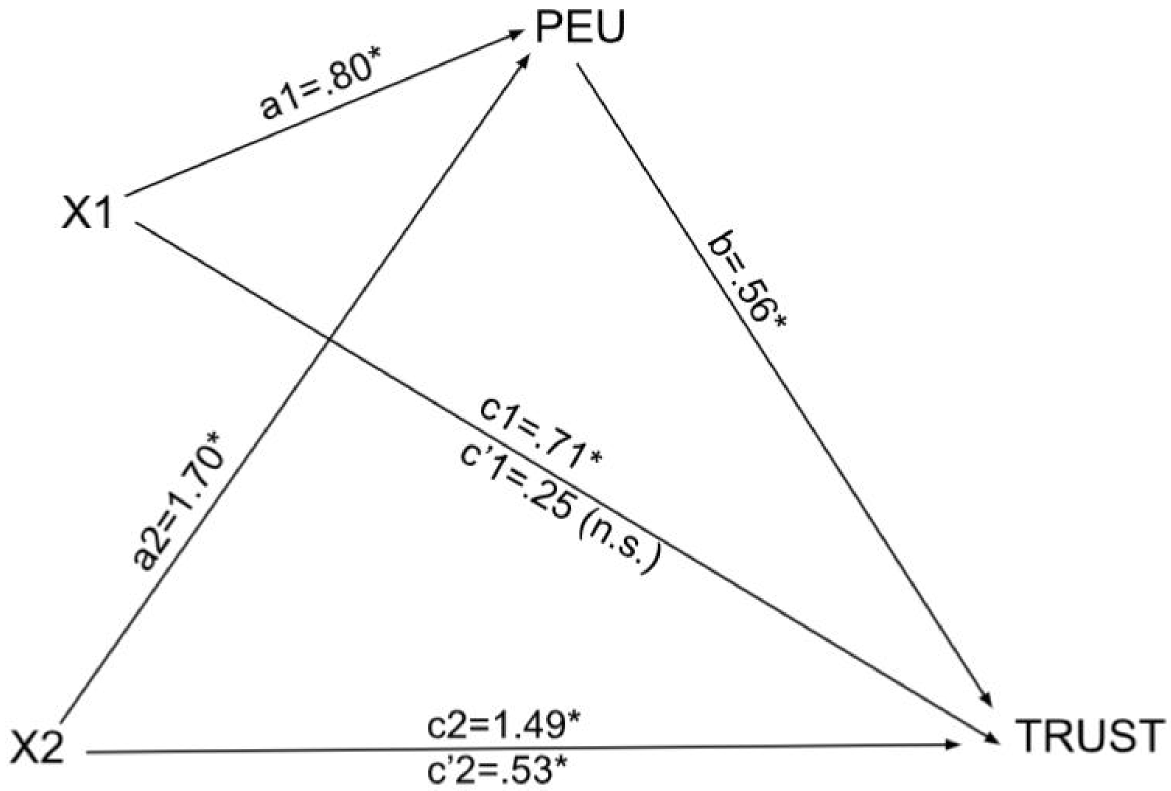


Figure 4-2. Mediation model showing the effect of AI interactivity on trust via Perceived Ease of Use (PEU).

4.2.4 Hypothesis 4: Trust Positively Predicts Consumers' Purchase Intention.

To evaluate Hypothesis 4, which proposed that consumers' trust in the AI streamer would positively predict their purchase intention, a simple linear regression analysis was performed. In this model, trust was entered as the independent variable, and purchase intention served as the dependent variable.

The regression model was highly significant,

$F(1, 155) = 509.39$, $p < .001$, with an R^2 value of .767, indicating that 76.7% of the variance in purchase intention could be explained by participants' trust in the AI streamer. This represents a large effect size, suggesting that trust is a major determinant of consumer behavioral intention in this context. The standard error of the estimate was 0.75, showing relatively low prediction error given the model's strength.

Examining the regression coefficients, the unstandardized coefficient for trust was $B = 0.95$, with a standard error of 0.04, yielding a t-value of 22.57 ($p < .001$). The standardized coefficient was $\beta = .88$, again confirming the strong effect. This means that for every one-point increase in trust (on a 7-point Likert scale), the predicted purchase intention increases by nearly one unit (0.95), holding all else constant. The regression intercept was B = -0.19, but it was not statistically significant (p = .27), indicating that when trust is zero, the baseline level of purchase intention is statistically indistinct from zero.

Table 4-3. Simple Linear Regression Predicting Purchase Intention from Trust in AI Streamer

Predictor	B	SE	β	t	p
Trust	0.95	0.04	.88	22.57	<.001
Constant	-0.19	0.17	—	-1.10	.272

Note. N = 157. Trust and purchase intention measured on 7-point Likert scales. B = unstandardized coefficient; β = standardized coefficient.

Altogether, the findings provide strong empirical support for Hypothesis 4. Trust in the AI streamer is not only significantly related to purchase intention but emerges as a particularly powerful predictor. These results highlight that consumers are much more likely to act on an AI streamer's recommendations when they perceive it as trustworthy, reinforcing the critical role of trust in AI-mediated commerce and persuasive digital environments.

Table 4-4 provides a summary of the four proposed hypotheses, including the predicted relationships, tested variables, and final outcomes based on statistical results.

Table 4-4. Summary of Hypothesis Testing Results

Hypothesis	Description	Result	Mediation Type
H1	AI interactivity positively affects trust	Supported	–
H2	PU mediates the effect of AI interactivity on trust	Supported	Full mediation

H3	PEU mediates the effect of AI interactivity on trust	Partially supported	Partial mediation
H4	Trust positively predicts purchase intention	Supported	–

Note. PU = Perceived Usefulness; PEU = Perceived Ease of Use.

Hypotheses were tested using ANOVA, linear regression, and Hayes' PROCESS macro (Model 4) with 5,000 bootstraps.

5. Discussion and Conclusion

5.1 Summary of Findings.

This study investigated how AI streamer interactivity influences consumer trust and purchase intention in the context of e-commerce live streaming. Grounded in the Technology Acceptance Model (TAM), Social Presence Theory, and Personalization Theory, the research tested four hypotheses using a between-subjects experimental design, in which AI streamer interactivity was manipulated at three distinct levels: low, medium, and high.

The statistical analyses confirmed that all four hypotheses were supported. These findings highlight that AI streamers are not merely functional tools for product delivery but can act as social agents whose communication style meaningfully shapes consumer trust and purchasing behavior.

The one-way ANOVA results revealed a clear positive trend: participants in the high interactivity condition reported significantly higher trust levels than those in the medium and low interactivity groups. Each group difference was statistically significant, demonstrating that increased interactivity—characterized by frequent responses and personalized engagement—substantially enhances consumer trust.

Further mediation analysis clarified the underlying mechanism. Specifically, the effect of AI interactivity on trust was found to be fully mediated by perceived usefulness (PU). When PU was included in the model, the direct effect of interactivity on trust became non-significant, while the indirect effect through PU remained statistically significant. This suggests that interactivity builds trust primarily because consumers perceive the AI streamer as helpful and informative. Once this sense of usefulness is accounted for, interactivity alone no longer directly influences trust.

Perceived ease of use (PEU) also contributed to trust formation. The results showed that interactivity made the AI streamer feel more intuitive and enjoyable to engage with, which in turn increased trust. However, even after controlling for PEU, the direct effect of interactivity on trust remained significant. This indicates that ease of use partially mediates the relationship, but additional factors—such as perceived personalization or social presence—likely play a role in trust formation as well.

Lastly, trust in the AI streamer was found to be a strong predictor of purchase intention. Trust explained 76.7% of the variation in participants' willingness to buy the recommended products (β = .876). This suggests that consumers who believe in the AI streamer construct are significantly more likely to follow its sales recommendations.

Collectively, these findings provide strong evidence that AI interactivity increases consumer confidence and willingness to buy, not only by enhancing functional and functionally related antecedents such as perceived usefulness and perceived ease of use, but also by influencing the social and emotional dimensions of interaction. In this sense, AI streamers can be viewed as technological devices as well as social actors capable of exerting various influences on consumer behaviour at multiple levels.

5.2 Theoretical Implications.

This study integrates and extends key theories in technology acceptance and online communication to explain how AI streamer interactivity influences consumer trust and purchase intention.

One fundamental explanation lies in the concept of social presence. Short et al. (1976, pp. 65 – 66) define social presence as the extent to which a communication medium enables users to experience others as psychologically present and socially engaged. Extensive research in online contexts (Gefen & Straub, 2003) confirms that increased social presence enhances consumer trust. In this study, highly interactive AI streamers—characterized by real-time responses, personalized engagement, and simulated human warmth—likely amplified this psychological closeness, thereby increasing their perceived credibility and trustworthiness. This finding contributes to the existing literature by demonstrating that interactivity itself, even when delivered via scripted video, can serve as a powerful social presence cue that significantly strengthens trust in AI agents.

The mediation results offer further theoretical insight by linking these findings to the Technology Acceptance Model (TAM). Davis (1989, p. 320) emphasized that perceived usefulness (PU) and perceived ease of use (PEU) are critical predictors of technology acceptance. In this study, PU fully mediated the effect of AI interactivity on trust, while PEU partially mediated it. This supports Davis (1989) assertion that PU is a primary determinant of user acceptance. Specifically, participants trusted AI streamers more when they perceived them as helpful in achieving their goals or making better purchase decisions. Interactive AI streamers likely delivered greater perceived value through timely, personalized responses and engaging communication, thereby elevating their perceived usefulness.

This study extends Davis (1989, p. 320) original workplace-oriented PU concept to the consumer context of live-stream shopping, where perceived usefulness similarly shapes user trust. Additionally, the results align with integrative models of technology adoption that highlight trust as a critical predictor of behavioral intention. Gefen et al. (2003) demonstrated that in online shopping, trust is as influential as PU and PEU in predicting consumer behavior. The present study supports this integrated view by showing that an AI streamer's perceived usefulness directly strengthens user trust, which in turn drives purchase intention.

The partial mediation by PEU provides a more nuanced understanding. Interactivity appeared to enhance PEU by making AI streamers feel more user-friendly, intuitive, and responsive, which can help users feel at ease. This is consistent with Davis (1989, pp. 326 – 327) assertion that systems perceived as easy to use foster positive user perceptions and higher engagement. However, the continued direct effect of interactivity on trust, even after accounting for PEU, suggests that AI interactivity delivers additional benefits beyond usability, such as increased enjoyment and emotional connection.

This perspective is reinforced by Social Presence Theory, which emphasizes that different media vary in their ability to create psychological closeness and the sense of "being with" another person (Short et al., 1976, pp. 13 – 14). Highly interactive AI streamers, through real-time, personalized responses, can deliver strong social presence cues that make them appear more human-like and trustworthy.

Moreover, the findings resonate with Komiak and Benbasat's (2006) research on intelligent agents, which emphasized that trust develops through both rational evaluations of an agent's competence and emotional rapport. Their work demonstrated that emotional trust can fully mediate the influence of cognitive trust on technology adoption, underscoring the importance of dual cognitive and emotional trust pathways. This study supports that dual-process view: perceived usefulness (a cognitive evaluation) and the interactive, humanized experience (which fosters emotional connection) jointly build overall user trust.

Trust was also found to be a strong predictor of purchase intention. According to TAM, improved perceptions of usefulness and ease of use are expected to culminate in stronger behavioral intentions (Davis, 1989). This study extends that logic by positioning trust as a direct driver of purchase intention in AI live-streaming commerce. The findings are consistent with previous research emphasizing that trust is one of the most powerful predictors of users' intent to adopt new technologies, especially in online purchasing contexts (Gefen et al., 2003). Gefen et al. further demonstrated that trust can sometimes outweigh perceived usefulness in driving purchase decisions.

Komiak and Benbasat (2006) also confirm the importance of trust in the acceptance of recommending agents, particularly in personalized and intelligent recommendations. They underline that trust comprises cognitive as well as affective aspects, including within artificial intelligence-based consumer interactions.

In this research, trust explains a large proportion of the total variance in purchase intention, collectively suggesting that trust is a paramount factor in consumers' consideration of whether to follow the AI streamer's recommendations. In theory, this implies that, in the context of AI influencers or virtual agents, trust could be considered a direct antecedent impacting consumer behavior, as it is considered in the original TAM constructs.

Such findings contribute to a fully-fledged theoretical account: shared features of interactive technology comprise both cognitive (e.g., perceived usefulness and ease of use) and social-emotional elements (e.g., social presence) that lead to trust and intention to purchase. Furthermore, these findings are also in line with Personalization Theory, known for stating that personalized services result in higher user engagement and trust. If AI streamers provide personalized, context-aware responses, users may experience greater social presence and relevance—facilitating the building of trust in digital communication. This correlation suggests that personalization techniques can not only enrich functional evaluations but also enhance emotional perception and foster the development of social attachment (an early conception of trust in AI streamers).

5.3 Practical Implications.

The results of this study have important implications for e-commerce platforms that seek to enhance consumer trust and purchase intention through AI-generated livestreaming views. One noteworthy implication of the findings is that developing AI streamers that provide high interactivity, individualized responses, and simple user interfaces is the most effective way to increase consumers' trust and purchase intention, which is the central conclusion of this study.

First, these AI streamers need to be developed to provide real-time contextual responses in personal conversations and spontaneous comments. These features are crucial for the construction of perceived social presence and trust in consumer-to-consumer commerce (Short, Williams, & Christie, 1976, pp. ix – xii). When AI streamers actively engage users, they can create a sense of "being with" another person, which enhances credibility and emotional connection. Practical implementation could involve AI streamers that greet users, respond to comments promptly, and pose individualized questions that encourage interactive dialogue.

Second, personalization strategies are crucial for building trust and enhancing consumer engagement. Chattaraman, Kwon, and Gilbert (2012) demonstrated that virtual agents offering tailored support significantly increase perceived social support and trust, especially among users who may face barriers to technology adoption. Their study highlighted that virtual agents providing search and navigation assistance in online stores not only foster trust but also strengthen patronage intentions. Applying these insights to AI streamers suggests that when they deliver context-aware, user-specific interactions, they can effectively reduce psychological distance and foster stronger consumer relationships.

Third, ease of use and interface usability remain fundamental in shaping positive consumer responses. In the common understanding of integrated TAM-trust models—and perhaps less obviously—system usability (i.e., easy navigation and intuitiveness) is highly related to increased levels of trust (Gefen, Karahanna, & Straub, 2003). Interactivity alone is not enough for AI streamers; they must also be user-friendly and efficient to ensure an uninterrupted interaction experience. Simple interfaces, communicative cues, and low cognitive load are important design considerations.

For e-commerce companies, an aggregated reading of these findings highlights the need to invest in AI streamers that possess social and engaging qualities, are deeply personalized, and operate with minimal friction. Such designs can greatly improve the user experience and increase purchase conversion in AI-generated live commerce.

5.4 Limitations.

5.4.1 Controlled scenario.

This study employed scripted video clips to present three distinct levels of AI streamer interactivity: low, medium, and high. While this controlled design effectively isolated the independent variable, it may have limited ecological validity. Norman's (2013, pp. 45 – 46) discussion on how design cues influence user perceptions inspired the current study to consider additional factors, such as tone of voice and visual presentation, when evaluating consumer trust in AI streamers. By holding these cues constant, the study may not fully capture how consumers respond to interactive AI streamers in authentic commercial environments.

5.4.2 Self-reported measures.

Participants evaluated their trust and purchase intention immediately after watching the video using self-report Likert scales. Although efficient, this method primarily captures immediate reactions. In real-world e-commerce settings, trust and purchase decisions typically develop progressively over time (Pavlou & Gefen, 2004). Furthermore, self-reported purchase intentions do not always predict actual buying behavior (Sniehotta, Presseau, & Araújo-Soares, 2014). Future studies would benefit from employing longitudinal designs or incorporating behavioral data to track trust development and purchasing actions in more naturalistic contexts.

5.4.3 Sample and generalizability.

This study utilized snowball sampling, primarily recruiting participants from the researcher's social network, which included university students, friends, and acquaintances. Although snowball sampling is valuable for accessing special populations, it is not uncommon for this sampling method to carry the risk of sample bias and limited generalizability of the results (Goodman, 1961). As a result, the sample—while representative of the target population of the survey—was biased toward younger, better-educated individuals and those with higher digital literacy. While this sample was informative for a pilot study, it may not generalize to the broader population.

Previous research has indicated that consumer reactions to technology differ greatly by age as well as by education level (Mitzner et al., 2019). For example, younger participants may find highly interactive AI streamers to be more exciting and believable (Prensky, 2001), whereas older participants might prefer organized and predictable interactions (Chattaraman, Kwon, & Gilbert, 2012). In addition, previous experience with AI and livestream commerce might influence consumers' ability to interpret interactive and trust-related cues (de Visser et al., 2016). The strength of these effects is most likely moderated by demographic factors such as age, education, AI familiarity, and livestream shopping frequency, which warrants systematic investigation in future research.

Another limiting factor is that only one product category was used in a single shopping situation. Consumer reactions to AI streamer interactivity might not be uniform across product types or decision-making contexts. Consumer behavior could vary significantly depending on the level of product involvement and perceived purchase risk

(Goldsmith & Flynn, 2014, p. 270). Furthermore, it would be interesting to investigate whether the effects of AI interactivity are consistent across various product categories and shopping scenarios.

5.4.4 Measurement Validity.

Another limitation is the modification of the PU measurement items. Davis' (1989) original PU scale was created to measure performance enhancement in utilizing job-related technology applications. In the present study, the PU construct was adapted to measure consumer perceptions of product understanding and shopping assistance in a livestreaming context. While this adaptation was necessary to fit the study setting, it may have had the unintended effect of recentering (‘neutralizing') the core meaning of the construct—from performance enhancement to decision clarity and consumer assistance.

This might also lead to issues related to construct validity, as the adapted items may not fully capture the original theoretical concept of "usefulness" in the Technology Acceptance Model. This concern could be alleviated by testing and developing PU scales that are specifically aligned with AI-based consumer shopping experiences. Doing so would ensure that the measurement remains theoretically grounded and appropriately reflects consumer-perceived usefulness in AI-assisted purchase situations.

5.5 Future Research Directions.

Building on this study's findings and acknowledging its limitations, several future research directions are recommended to further advance the understanding of AI streamer interactivity and its impact on consumer trust and behavior.

5.5.1 Using real-time AI interaction.

This study utilized pre-recorded video clips to manipulate levels of AI interactivity in a controlled setting. While this method provided clarity in isolating the independent variable, it did not replicate genuine two-way communication. Future research should incorporate real-time, interactive AI streamers that can directly engage with users in unscripted, dynamic interactions. Real-time interaction would offer a more ecologically valid environment and provide insights into whether live engagement continues to build consumer trust when users can actively participate.

5.5.2 Testing social presence as a mediator.

Although this study focused on perceived usefulness (PU) and perceived ease of use (PEU) as mediators, social presence may also be a key psychological mechanism explaining how interactivity builds trust. Future studies could directly measure users' perceptions of social presence, including feelings of connection, human-likeness, and emotional warmth during AI interactions. Examining social presence as a mediator would offer a deeper understanding of the social processes that contribute to trust in AI-driven livestreams.

5.5.3 Exploring other mediators and moderators.

Future research should investigate other psychological mechanisms that may explain the trust-building process. For instance, perceived enjoyment could serve as a mediator, as users who find AI interactions enjoyable may develop trust more readily, beyond functional assessments like PU and PEU.

Additionally, individual differences should be considered as potential moderators. Prior trust in AI technology may significantly influence how consumers perceive and respond to AI streamers. Those with more positive prior experiences may develop trust faster, whereas skeptical users may need stronger interactive cues (de Visser et al., 2016).

Product category familiarity could also moderate the effects of interactivity. Consumers less familiar with a product may rely more on the AI streamer's trustworthiness, while those familiar with the product may be less influenced by interactivity (Chattaraman et al., 2019).

Moreover, technology adoption tendencies—such as openness to innovation, digital literacy, and past use of AI systems—could shape how users respond to AI interactivity (Venkatesh & Davis, 2000). Including these moderators would enable a more nuanced exploration of when and for whom AI interactivity is most effective.

5.5.4 Conducting longitudinal and behavioral research.

This study measured trust and purchase intention immediately following a single exposure. Future research should adopt longitudinal designs to track whether trust in AI streamers is sustained, strengthened, or diminished over repeated interactions. Furthermore, behavioral data—such as actual purchasing behavior in AI livestreams—should be incorporated to assess whether self-reported intentions translate into real-world actions, thereby enhancing the practical validity of the findings.

5.5.5 Comparing AI streamers with human streamers.

Future studies could compare AI streamers with human influencers to explore whether users build trust through similar mechanisms. Investigating whether interactivity has comparable effects across AI-human and human-human livestreams would test the generalizability of key theories like the Technology Acceptance Model (TAM) and Social

Presence Theory. Such comparisons could reveal whether human-likeness remains a critical factor or if AI streamers can independently establish trust and persuasive power in digital marketing contexts.

In conclusion, this study offers clear evidence that interactive technology features significantly shape consumer perceptions and behaviors through both functional and social pathways. By demonstrating that AI streamer interactivity enhances perceived usefulness, ease of use, and social presence—ultimately building trust and driving purchase intentions—this research advances theoretical understanding in AI-driven commerce. The findings contribute to the integration of the Technology Acceptance Model with trust and social presence frameworks, providing a comprehensive view of user engagement with AI-based virtual agents.

Furthermore, this study emphasizes that well-designed AI streamers—those that interact dynamically, provide personalized experiences, and are perceived as useful and user-friendly—can meaningfully influence consumer trust and purchase decisions. As AI technologies evolve, developing interactive, socially engaging, and trustworthy virtual agents will be essential for businesses seeking to establish strong and enduring consumer relationships in digital environments.

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Appendix A Original Survey

您好！感谢您点击参与本次问卷调查。
问卷旨在协助我完成我在鹿特丹伊拉斯姆斯大学（Erasmus University Rotterdam）的一项研究课题，主题涉及人们在观看AI主播带货直播时的感受与态度。
问卷中，您将：
* 提供一些基础信息（仅用于统计分析，如性别、年龄）
* 回答有关您观看电商直播习惯的问题
* 观看一段约1分钟的直播视频片段
* 根据观看体验，填写几个简短问题

🔒 隐私声明与自由参与权：
* 本问卷不收集您的任何身份信息（如姓名、联系方式等）
* 所有数据仅用于学术研究，并将严格保密处理
* 您可随时中止填写，不会对您产生任何不良后果
* 没有“对”或“错”的答案，请根据您的真实感受作答即可

整个填写过程大约耗时5–7分钟，非常感谢您的时间与支持！
如您准备好，请点击“下一步”开始。 祝您填写愉快！
——研究者 敬上

您的性别是?

- ◯ 男
- ◯ 女
- ◯ 其他
- ◯ 不愿透露

*您的年龄是？（仅输入数字）

您的性别是?

◯ 男

◯ 女

◯ 其他

◯ 不愿透露

ⓘ 请输入有效的数字。

*您的年龄是?（仅输入数字）

转到页尾 >

您的最高学历（含在读）是?

◯ 高中及以下

◯ 大专

◯ 本科

◯ 硕士及以上

您是否观看过AI主播的直播?

◯ 是

◯ 否

您观看电商直播的频率?

◯ 从不观看

◯ 偶尔（每月1–2次）

◯ 经常（每周1–2次）

◯ 很频繁（每周3次及以上）

您每次观看直播的平均时长?

◯ 少于10分钟

◯ 10–30分钟

◯ 30–60分钟

◯ 超过1小时

您通过直播购物的倾向性如何?

0 —————————— 100

系统将在下页为您随机播放一段1分钟的AI主播带货片段，请您像平时看直播一样自然观看。视频结束后请回答相关问题。
如果视频播放效果不佳，请按视频右下角调整至全屏播放，或跳转到Bilibili进行观看。

综合您的观看体验，以下哪一项最符合您对该主播互动水平的总体印象?

◯ 这位主播几乎没有互动，只是在单方面介绍产品，几乎不回应观众的问题。

◯ 这位主播偶尔回应观众的问题，互动频率不高，也不太具有个性化。

◯ 这位主播回应迅速，与观众互动频繁，且回应内容具有针对性和个性化。

请根据您观看直播的体验，评价下列陈述是否符合您的感受。
每题均为 Likert 7分制：1 = 完全不同意，7 = 非常同意

请您评价以下有关“AI主播是否对购物有帮助”的陈述：

	完全不同意				非常同意		
	1	2	3	4	5	6	7
通过这个 AI 主播的讲解，我可以更高效地了解产品信息。	○	○	○	○	○	○	○
有了这个 AI 主播的推荐，我觉得选购商品变得更加高效省时。	○	○	○	○	○	○	○
总体而言，这个 AI 主播的带货直播对我的网购很有帮助。	○	○	○	○	○	○	○

以下问题想了解您对“与该AI主播互动是否轻松容易”的看法：

	完全不同意				非常同意		
	1	2	3	4	5	6	7
了解如何观看和参与这个 AI 主播的直播对我来说是容易的。	○	○	○	○	○	○	○
与这个 AI 主播进行互动非常简单明了。	○	○	○	○	○	○	○
整体来说，使用这个 AI 主播的直播过程是轻松无压力的。	○	○	○	○	○	○	○

请您评价以下关于“您对该AI主播的信任程度”的陈述：

	完全不同意				非常同意		
	1	2	3	4	5	6	7
我认为这位 AI 主播是值得信任的。	○	○	○	○	○	○	○
我相信这位 AI 主播在介绍产品时是诚实的，不会夸大其词。	○	○	○	○	○	○	○
我觉得这位 AI 主播提供的产品信息是可靠的，不会误导消费者。	○	○	○	○	○	○	○
总体来说，我愿意依赖这位 AI 主播的推荐来帮助决策。	○	○	○	○	○	○	○

以下陈述希望了解您对"是否愿意购买该主播推荐产品"的看法：

	1 完全不同意	2	3	4	5	6 非常同意	7
听取了这位 AI 主播的介绍后，我产生了购买该产品的打算。	○	○	○	○	○	○	○
我很可能会购买这位 AI 主播推荐的商品。	○	○	○	○	○	○	○
在未来，我计划根据这位 AI 主播的推荐来购买商品。	○	○	○	○	○	○	○
如果有机会，我愿意尝试购买AI主播在直播中介绍的其他商品。	○	○	○	○	○	○	○

🎉 **感谢您的参与！**
您已完成本次调查，再次诚挚感谢您抽出宝贵时间！
现在，我们想向您简要介绍本研究的真实意图：
本研究旨在探讨**不同互动水平的AI主播**在电商直播中的表现，是否会影响观众对主播的**信任感**，以及这是否进一步影响他们的**购买意愿**。
这项研究希望帮助我们更深入理解AI技术在人机互动和消费者行为中的作用。
您的回答将为这一研究提供宝贵的数据支持，帮助我们从学术视角分析AI主播在商业环境中的潜在影响。
🔒 您的所有回答都将严格保密，仅用于学术研究，不涉及任何商业用途。
如您对本研究有任何疑问，或者有兴趣了解后续进展，欢迎随时联系我：
📩 732157jz@eur.nl
再次感谢您的参与与支持！
祝您生活愉快！
——研究者 敬上

Appendix B Translated Survey - English Version

Hello! Thank you for clicking to participate in this questionnaire. The questionnaire aims to assist me in completing a research project at Erasmus University Rotterdam. The theme involves people's feelings and attitudes when watching live - streaming sales with AI hosts. In the questionnaire, you will:
* Provide some basic information (only used for statistical analysis, such as gender, age)
* Answer questions about your habits of watching e - commerce live - streaming
* Watch a live - streaming video clip of about 1 minute
* Fill in a few short questions based on your viewing experience

🔐 Privacy Statement and Right to Free Participation:
* This questionnaire does not collect any of your identity information (such as name, contact information, etc.)
* All data is only used for academic research and will be strictly confidential
* You can stop filling out at any time without any adverse consequences
* There are no "right" or "wrong" answers. Please answer according to your true feelings.

The entire filling process takes about 5 - 7 minutes. Thank you very much for your time and support! If you are ready, please click "Next" to start. Wish you a pleasant filling experience!
——Sincerely, the researcher

What is your gender?

◯ Male

◯ Female

◯ Others

◯ Prefer not to say

*What is your age? (Enter numbers only)

What is your gender?

- ◯ Male
- ◯ Female
- ◯ Others
- ◯ Prefer not to say

ⓘ Please enter a valid number.

*What is your age? (Enter numbers only)

Go to end of page >

What is your highest educational attainment (including current enrollment)?

- ◯ High school or below
- ◯ Associated Bachelor
- ◯ Bachelor
- ◯ Master's degree or above

Have you ever watched a live stream of an AI anchor?

- ◯ Yes
- ◯ No

How often do you watch e-commerce live streams?

- Never
- Occasionally (1 - 2 times a month)
- Often (1 - 2 times a week)
- Very frequently (3 times a week or more)

What is the average duration of each live stream you watch?

- Less than 10 minutes
- 10–30 minutes
- 30–60 minutes
- More than 1 hour

How likely are you to shop through live streaming?

0 100

The system will randomly play a 1 - minute live - streaming e - commerce clip by an AI host on the next page. Please watch it as naturally as you do when watching a live stream. After the video ends, please answer the relevant questions. If the video playback effect is not good, please click the lower - right corner of the video to adjust it to full - screen playback, or jump to Bilibili to watch.

Based on your viewing experience, which of the following best matches your overall impression of the streamer's interaction level?

- This streamer has almost no interaction. They are just unilaterally introducing products and hardly respond to the audience's questions.
- This streamer occasionally responds to the audience's questions. The interaction frequency is not high, and it is not very personalized.
- This streamer responds quickly, interacts frequently with the audience, and the response content is targeted and personalized.

Please evaluate whether the following statements are consistent with your feelings based on your live - streaming viewing experience. Each question uses a Likert 7 - point scale: 1 = Strongly disagree, 7 = Strongly agree

Please rate the following statements regarding "Whether AI anchors are helpful for shopping":

	Completely disagree 1	2	3	4	5	Completely agree 6	7
With this AI streamer's recommendation, I felt that choosing a product became more efficient.	○	○	○	○	○	○	○
With this AI streamer's recommendation, I felt that choosing a product became more efficient.	○	○	○	○	○	○	○
The AI streamer helps me make better product choices during online shopping.	○	○	○	○	○	○	○

The following questions aim to understand your views on "Whether it is easy to interact with this AI host":

	Completely disagree 1	2	3	4	5	Completely agree 6	7
It was easy for me to understand how to watch and engage with this AI streamer's livestream.	○	○	○	○	○	○	○
Interacting with this AI streamer was easy to follow.	○	○	○	○	○	○	○
Overall, engaging with this AI streamer during the livestream felt relaxed and effortless.	○	○	○	○	○	○	○

Please rate the following statements regarding "Your level of trust in this AI anchor":

	Completely disagree				Completely agree		
	1	2	3	4	5	6	7
I believe this AI streamer is trustworthy.	○	○	○	○	○	○	○
I trust that this AI streamer is honest when introducing products and does not exaggerate	○	○	○	○	○	○	○
I find the product information provided by this AI streamer to be reliable and not misleading	○	○	○	○	○	○	○
Overall, I am willing to rely on this AI streamer's recommendations to assist my decision-making.	○	○	○	○	○	○	○

The following statements aim to understand your opinion on "whether you are willing to buy the products recommended by this streamer":

	完全不同意				非常同意		
	1	2	3	4	5	6	7
After hearing this AI streamer's introduction, I am considering purchasing the product.	○	○	○	○	○	○	○
I am likely to purchase the product recommended by this AI streamer.	○	○	○	○	○	○	○
In the future, I plan to buy products based on this AI streamer's recommendations.	○	○	○	○	○	○	○
If I get the chance, I am willing to try other products introduced by this AI	○	○	○	○	○	○	○