

Unveiling the impact of human and AI-broadcast on impulsive consumption Mediating role of consumer engagement and moderating role of social overload

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Abstract: This study compares the effects of AI and human broadcasters on consumer engagement, trust, satisfaction, and impulsive consumption in live-streaming e-commerce. Drawing on the Stimulus–Organism–Response (S-O-R) framework, broadcaster type is conceptualised as the stimulus, perceived status elevation and Consumer senses are examined as organismic states, and impulsive consumption is treated as the behavioural response. Social overload is incorporated as a moderating condition. A quantitative survey design was adopted, and data were collected from consumers with experience in AI- and human-led live-streaming commerce. The proposed model was tested using PLS-SEM and multi-group analysis to examine direct, mediating, and moderating effects. The results show that both AI and human broadcasters positively influence perceived status elevation and Consumer senses. Human broadcasters exert a stronger effect on Consumer senses, whereas AI broadcasters provide more structured and consistent interaction cues. Social overload positively moderates the relationship between AI broadcasters and Consumer senses. Social overload also positively moderates the relationship between human broadcasters and Consumer senses. In addition, social overload moderates the relationship between Consumer senses and consumer engagement only in the human broadcaster group. Trust and consumer satisfaction significantly predict impulsive consumption in both groups, while consumer engagement predicts impulsive consumption only in the human broadcaster group. This study contributes to live-streaming commerce research by directly comparing AI and human broadcasters within an integrated mediation–moderation framework. It clarifies how broadcaster type shapes consumer responses through perceived status elevation, Consumer senses, satisfaction, engagement, and trust, while also showing the context-dependent role of social overload.

Keywords: AI broadcasters, Consumer senses, Human broadcasters, Impulsive consumption, Live-streaming e-commerce, Perceived status elevation, Social overload, Trust.

1. Introduction

Live Streaming Ecommerce is rapidly turning the digital economy into a platform of real-time interaction and social networking for online shopping. Compared with traditional e-commerce, that emphasize on efficiency and convenience. Live-streaming e-commerce gives a lively feel where customers can observe moving pictures of goods, converse with the broadcaster, and with other watchers. This very engaging social setting can lead to trust being formed quickly and cuts down the time needed for purchasing decisions, thereby boosting both kinds of unplanned and planned purchasing behaviour [1, 2].

With AI advancing as time goes by, it feels like on these platforms now there is going to be an AI broadcaster. AI broadcasters deliver consistently reliable experiences and manage high volumes of consumer interaction efficiently. While AI broadcasters excel in speed and reliability, human broadcasters retain the capacity to evoke emotions; they can make personal, spontaneous interjections

with gestures and words [3]. As an increasing number of platforms adopt both AI and human presenters, understanding the relative impact of each broadcaster type on viewer behaviour has become a central question in digital commerce research.

This research uses the S-O-R model [4] that treats broadcaster types as external stimuli resulting in internal customer responses. About this framework, the on-camera presenters, whether AI presenters or human presenters, invoke states like sensation, status increase, and ultimately affect vital behavioral outcomes such as trust, satisfaction, and impulse to purchase on impulse [3, 5]. Thus, there exists the opportunity for an extremely thorough review of the emotions and minds of viewers around during a live video stream.

Two organismic states are examined in this study. The first is perceived status elevation, the consumer's sense of being recognised and valued through live interaction. Regarding what has been studied so far, human speakers produce such emotions to a greater extent through empathy and adapting social signals [6]. Speaking of that, AI broadcasters are great and consistent, but they can't do subtle emotional feedback. The different types of broadcasters have very different consumer senses; consumer responses are shaped by the extent to which audiovisual stimuli capture attention and evoke emotional resonance; humans can express richer and more variable senses natively than AI can generate.

Social overload is another very important type, which means the overload of social stimulation from the digital world, the pressure from the brain, and emotions. And this moderator can totally change how customers answer the question: AI broadcasters would have much more predictable and structured forms of interaction, which is something that might be able to handle much higher levels of overload. Human broadcasters might be more potent if the load is low because people tend to feel spontaneous and warm [7].

Despite the growing body of literature, comparative research on AI and human broadcasters remains limited. Empirical evidence concerning their differential effects on trust, engagement, and impulsive purchasing is scarce and, where present, inconclusive. The moderating role of social overload also has a small number; the mediating role of perceived status rise and perceived consumer senses in satisfaction and impulsive consumption. And more is that there's no systematic study on the direct link between satisfaction and impulse buying in the livestreaming context.

To address these gaps, this study systematically compares the effects of AI and human broadcasters on Consumer senses, perceived status elevation, trust, satisfaction, and impulsive consumption. It places Consumer senses and perceived status elevation in a mediating role and social overload as a key moderating factor, thus giving an all-around framework to explain consumer choice in live-stream e-commerce. The results should bring the theory of consumer psychology out and give people who operate platforms or marketplaces that try to do real-time optimization on how their interaction with a buyer works some kind of actionable information.

2. Literature Review

2.1. Theoretical Foundation: Stimulus–Organism–Response (S-O-R) Model in Live Streaming Commerce

Stimulus–Organism–Response (S-O-R) model, by Mehrabian [4] has become a basic explanation model of how the environmental stimulations affect the consumers' inner feelings and produce some visible behavior. When it comes to livestream commerce, using the S-O-R perspective to see how things like AI/human external stimuli for broadcasters might make them feel status, or give them mental exertion or sensory arousal [3, 6]. Empirical studies demonstrate that the S-O-R framework is particularly effective in explaining consumer behaviour within interactive, mediated digital environments [2, 8]. Accordingly, this study uses the S-O-R model to explore how different types of broadcasters form the streaming consumers' feelings, views, and actions towards streaming shops.

2.2. Broadcaster Type and Perceived Status Elevation

PSE is about how others see them as being seen and respected in the eyes of those observing them on the live streaming exchange [9]. In streams directed at humans, PSE often results from relational cues such as calling out the viewer personally, giving individualized greetings, showing empathy toward the audience, and just being warm in an unscripted manner, making the meeting mean more than a transaction. Repeated exposure to these micro-affirmations sustains parasocial interactions; viewers understand the broadcaster's attention as real recognition of their status, their place within the community [6]. In other words, PSE represents having a psychological payoff of a human-led interaction.

AI broadcasters close this gap well. AI broadcasters employ anthropomorphic dialogue systems that remember user preferences and contextualize responses, delivering warm interactions through natural prosody and expressive visuals. The most important thing is that these types of recognition signals are coming in at a steady rate from an AI and on volume as well, not getting lost in conversations full of information where a human might feel overwhelmed [3, 10]. Such that consumers accept and respect them over time if these happen enough and often, and with those responses actually being there, people, that way, technologically mediated acknowledgments can accumulate perceptions of status through a distinct mechanism over years, not necessarily using the same medium.

H₁: AI broadcasters positively influence consumers' perceived status elevation.

H₂: Human broadcasters positively influence consumers' perceived status elevation.

2.3. Broadcaster Type and Consumer Senses

Consumer senses (CSe) refer to the extent to which consumers are absorbed by visual, auditory, and affective cues during live-streaming interactions. It refers to how many senses together create a single state of awareness and feeling. Earlier research shows that multisensory stimulation increases memory recall as well as intensifies the emotional response, which in turn improves consumer views on digital interactions [11].

In the realm of live-streaming commerce, human broadcasters effectively promote consumer senses (CSe). Human broadcasters employ varied facial expressions, vocal modulations, and move them spontaneously, with feeling. Collectively, these elements create a vivid, dynamic presentation. This sense of immediacy fosters perceived authenticity, enabling viewers to feel integrated into an ongoing, uninterrupted experiential flow. In addition to visual and auditory stimuli, people's expressive feeling of infectiousness can also make the product demonstration more resonant [12]. As a result, the sensorial engagement with human broadcasters usually results in stronger affective attachment as well as sustained attention of the consumer.

In contrast, AI broadcasters lack emotional spontaneity; however, their principal advantage lies in delivering consistent, reliable, and well-controlled information. AI-created visuals are high-definition with a smooth feel, as well as having the same voice throughout to give the whole feeling of a seamless environment. When it's most valued for being reliable and clear, not varied and spontaneous [13, 14]. People who live in this surrounding space might love its sense of predictability, nondistractedness, knowing that an AI is always there, like a sort of mental assistant that helps them stay focused and understand. Thus, even though the means may be different, human announcers and AI announcers can make audiences feel that something is happening, but at different times.

H₃: Human broadcasters positively influence Consumer senses.

H₄: AI broadcasters positively influence Consumer senses.

2.4. The Moderating Role of Social Overload

Social overload (SO) arises when excessive social and informational demands overwhelm individuals, leading to exhaustion, irritability, and impaired cognitive processing and decision quality [7]. In live-stream commerce, with the constant flow of messages, quick sending, and immediate visual and acoustic signals, it is even more so. Exchanges between broadcasters and audiences become so lively

that audiences have to stick to the pace of exchange when it becomes too fast, thereby making their minds busy and taking away the space for them to participate and join in [15, 16]. It can therefore be seen that SO is a context that influences a consumer's interpretation and response to the live-stream environment.

It is within this context that broadcaster type assumes particular significance. AI broadcaster has a stable tempo, can reply in expected types, and keeps providing info to lessen uncomfortable overflow. It is due to their reliability that it allows for a rhythm of interacting with them that the audience can manage their own interest in how much time spent on them. It feels like they're immersion rather than just adding to the pile of confusion [8, 13]. Conversely, human broadcasters, who rely primarily on spontaneity and emotional expression, may experience greater strain in high-intensity sessions. These sorts of attributes can be useful when it isn't so intense an interval, yet they become amplifiers in the crowded area, making consumers get hit unexpectedly with emotional and informational overload.

Therefore, social overload is expected to shape two related mechanisms. First, it may condition how broadcaster type influences Consumer senses, because AI and human broadcasters differ in stability, spontaneity, and information delivery. Second, social overload may also influence whether Consumer senses is translated into active consumer engagement. Under high social overload, sensory cues may either intensify involvement by capturing attention or weaken engagement by increasing cognitive burden. Accordingly, this study proposes the following moderating hypotheses:

H₅: Social overload positively moderates the relationship between human broadcasters and Consumer senses.

H₆: Social overload positively moderates the relationship between AI broadcasters and Consumer senses.

H₈: Social overload positively moderates the relationship between Consumer senses and consumer engagement.

2.5. Perceived Status Elevation and Consumer Satisfaction

Consumer satisfaction (CSa) represents the evaluative outcome of interactions that meet or surpass a consumer's psychological expectations [17]. Within live-streaming commerce, satisfaction extends beyond functional performance to encompass the social and symbolic dimensions of interaction. A typical preceding condition is an increase in perceived status; at that time, a person feels more respected and included. When the viewers feel that they are respected in this way, their psychological needs for respect and belonging will be met, and they will be more satisfied with the streaming experience.

Human broadcasters are especially good at creating this effect; their personalized greetings, empathetic tones, and spontaneous responses can foster a stronger sense of closeness with the audience. Such relational gestures suggest that the consumer is not just one of many viewers but a person who has been recognized; thus, it increases their sense of satisfaction. AI broadcasters are less spontaneous but are now also generating more attention-grabbing content by adding anthropomorphic cues, consistent acknowledgments, and context-aware responses. Research shows that AI streamers are closer to being human, so most consumers have a better emotional response to them and are more likely to trust these streamers [3, 18].

Therefore, a state of higher psychological satisfaction is achieved through the inter-industry interactions of live-streaming activities for consumers.

H₇: Perceived status elevation positively influences consumer satisfaction.

2.6. Consumer Senses and Consumer Engagement

Consumer senses (CSe) enhance attentional depth by integrating visual, auditory, and affective cues in live-streaming interactions. Within the S-O-R framework, CSe is conceptualised as an organismic state (O) rather than a stimulus, because it captures consumers' internal sensory and affective responses to broadcaster-related stimuli. On a mechanistic level, rich sensory cues trigger attentional hijacks and emotional connections, which reduce competing cues, thereby improving the likelihood that consumers will comment, share, follow, or remain in-session longer [11].

In human-streamed videos, emotive speeches, sudden reactions, and flexible pitch result in lively multimodal signals that grab people's attention and draw them into the scene, transforming arousal into sustained participation [1, 2]. Not-planned pacing with unsteady timings, steady turn-taking, uniform pitch contours, and steady visual rhythms form an easily processed flow of interaction that maintains focus with few frequent interruptions with high density [19, 20]. Consumer senses thus represent the mechanism through which both human and AI broadcasters translate sensorial stimulation into observable, interactive consumer experiences.

H₉: The construct of Consumer senses positively influences consumer engagement.

2.7. Engagement, Trust, Satisfaction, and Impulsive Consumption

Trust is an important part of livestream commerce in the sense that many purchasers will be purchasing at a fast pace based on insufficient or unclear information. Consumer involvement was seen to improve perceived credibility by offering indicators of engagement and authenticity, which in turn improved trust in AI and human-guided interactions [2, 5]. Furthermore, sensory arousal and positive emotions drive purchase behaviour, thereby enhancing customer loyalty and reducing perceived risk. It can improve consumers' confidence.

Even satisfaction reinforces it. If a consumer's interaction results match or exceed their expectations, they will have better impressions and lower resistance against urgency cues and promotions. Satisfaction is cognitive certification, sentimental pledge; under the circumstance, it triggers unintentional acquisition and strengthens the link to the broadcasters. Empirical findings show that trust, satisfaction, etc., are very strong predictors of impulsive consumption, especially in a live-streaming environment characterized by immediacy, interactivity, and emotions [21].

And based on this reasoning, engagement, trust, and satisfaction are now acting as those critical organism's states between sensory and actions. Each pathway shows how human and AI broadcasters can use psychology to elicit impulsive consumption behaviour.

H₁₀: Consumer engagement positively influences trust.

H₁₁: Consumer satisfaction positively influences engagement.

H₁₂: Trust positively influences impulsive consumption.

H₁₃: Satisfaction positively influences impulsive consumption.

H₁₄: Consumer engagement positively influences impulsive consumption.

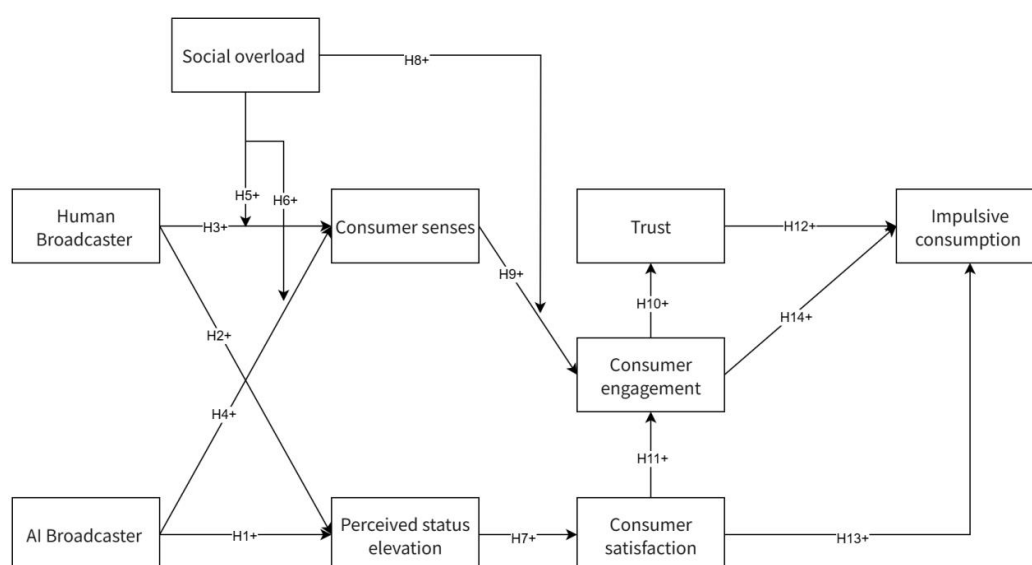


Figure 1.
The conceptual framework.

Figure 1 depicts the conceptual framework comparing AI and human broadcasters in live-streaming commerce. Based on the Stimulus–Organism–Response (S-O-R) model, broadcaster type serves as the stimulus, while perceived status elevation, consumer senses, consumer satisfaction, consumer engagement, and trust represent organismic states. Impulsive consumption is treated as a behavioural response. The model also incorporates social overload as a moderating variable, examining whether it conditions the effects of broadcaster type on consumer senses and the relationship between consumer senses and consumer engagement. In short, impulsive consumption is the result of satisfaction, engagement, and trust working together; it reflects the interplay of cognitive and affective processes that alter normative decision-making patterns and prompt immediate purchase behaviour following livestream interactions. This framework provides a theoretical foundation for subsequent experiments and analysis.

3. Research Methodology

This section describes the research models and hypotheses to support the current study, which evaluates the comparative impact of AI and human broadcasters on consumer behaviour in live-streaming e-commerce. The chapter uses Stimulus-Organism-Response (S-O-R) as its foundation to show the links from the type of broadcaster (AI vs. human) to mental processes like perception of sensation, rise in status, trust, satisfaction, immersion, and impulsive consumption. The model reflects digital commerce development in recent years, and conforms to the developing standards for the behaviour research field.

3.1. Research Design

A quantitative, cross-sectional design was used to empirically investigate consumer reactions in real-time live-streaming commerce surroundings. It allows for a strong examination of the relationship between focal constructs at a given single time point [22]. PLS-SEM is best suited for complex, multiple-variable models, where both direct and indirect (mediation) as well as moderator effects can be analyzed.

Consistent with the S-O-R framework, broadcaster type (AI vs human) was considered an exogenous stimulus, where organismic state was gauged through consumer senses, perceiving status elevation, engaging, trusting, and satisfying; behavioral response was reflected in impulsive consumption. The model explicitly takes into account social overload as a moderator, considering the cognitive demands usually met in highly interactive digital environments [7, 23]. In terms of methodological choices, current related research on stream-commerce and human-computer interaction was consulted [2, 6].

3.2. Sampling and Data Collection

A purposive sampling approach was employed to recruit participants who can provide insight based on their own experience in live-streaming commerce. This means participants should have interacted or participated in the purchasing process for a live-streaming commerce session hosted either by an AI or a human broadcaster. The recruitment was carried out through Wenjuanxing (www.wjx.cn), which is a widely trusted online survey platform in China. The data collection period was from January to February 2024, yielding a total of 805 valid responses after excluding invalid, inattentive, and irrelevant submissions. The sample was divided into two cohorts: respondents who had engaged with AI broadcaster sessions ($n = 301$) and those with experience in human broadcaster sessions ($n = 504$). This stratified design ensured adequate representation of both broadcaster types and met the requirements for the sample size in SEM analysis [22].

The combined sample was approximately 56% female and 44% male, broadly comparable to national usage patterns [24]. Given that the two cohorts adopt different age brackets (AI group: 18–24/25–34/35–44/45–54/55+; Human group: 18–30/31–40/41–50/51+), age distributions are reported by group in Tables 1a–1b, rather than aggregated into a single band. A substantial share of respondents

reported having made an unplanned purchase during recent live-commerce sessions. Informed consent was obtained, and institutional ethical approval was secured before data collection. “Times” denotes the number of live-commerce purchases made via live-streaming platforms in the past three months. Respondents with “0 times” in the AI cohort reported prior exposure to AI-led sessions but no purchases within the three-month recall window.

Table 1a.

Demographic profile of the AI broadcaster group (N=301)

Demographics	Number of respondents (N=301)	Percentage (%)
Times		
0 times	17	5.60%
1-9 times	123	40.90%
10-19 times	86	28.60%
20-39 times	41	13.60%
More than 40 times	34	11.30%
Gender		
Male	165	54.80%
Female	136	45.20%
Age		
18-24 years	123	40.90%
25-34 years	85	28.20%
35-44 years	54	17.90%
45-54 years	39	13.00%
55 years or older	0	0.00%
Income		
Below 3,999	52	17.30%
4,000- 6,999	85	28.20%
7,000- 9,999	100	33.20%
10,000-14,999	37	12.30%
Above 15,000	27	9.00%
Consumption Level		
Less than 499	85	28.20%
□ 500- 999	118	39.20%
□ 1,000-1,999	56	18.60%
□ 2,000- 3,999	27	9.00%
□ 4,000 or more	15	5.00%
Like		
AI Broadcasters (e.g., virtual influencers, automated hosts)	96	31.90%
Human Broadcasters (real-person hosts with live interaction)	136	45.20%
No preference	69	22.90%

Table 1b.

Demographic profile of the human broadcaster group (N=504).

Demographics	Number of respondents (N=504)	Percentage (%)
Times		
0 times	0	0.00%
1-9 times	44	8.70%
10-19 times	90	17.90%
20-39 times	150	29.80%
More than 40 times	220	43.70%
Gender		
Male	191	37.90%
Female	313	62.10%
Age		
18-30 years	185	36.70%
31-40 years	138	27.40%
41-50 years	94	18.70%

51 years or older	87	17.30%
Income		
Below 3,999	56	11.10%
4,000– 6,999	109	21.60%
7,000– 9,999	160	31.70%
10,000–14,999	87	17.30%
Above 15,000	92	18.30%
Consumption Level		
Less than 499	60	11.90%
□ 500– 999	64	12.70%
□ 1,000–1,999	132	26.20%
□ 2,000– 3,999	149	29.60%
□ 4,000 or more	99	19.60%
Like		
Human Broadcasters (real-person hosts with live interaction)	287	56.90%
AI Broadcasters (e.g., virtual influencers, automated hosts)	142	28.20%
No preference	75	14.90%

Note: (Tables 1a–1b): “Times” indicates the number of live-commerce purchases in the past three months. “Income” denotes monthly personal income (CNY). “Consumption Level” is the average amount spent per viewing of live-streaming (CNY). The percentages do not add up to 100% because of rounding.

3.3. Measurement Instruments

All of the above indicators were translated into Chinese using standardised scales from the original study and checked for consistency in the Chinese version. All the indicators were rated on a scale of 1 to 5, where 1 meant “strongly disagree” and 5 meant “strongly agree”, and are commonly used in behaviour and marketing research [25]. To ensure the linguistic accuracy and context relevance for Chinese speakers, all items were translated and back-translated [26].

Broadcaster type (AI vs. Human) was identified by screening questions that classified participants' live-streaming experiences. Four items from Kamel et al. [27] were used to assess Consumer senses, and these were extended to cover audiovisual richness and immersive interaction in live-streaming. Choi et al. [6] developed five items to assess perceived status elevation and measured the sense of recognition and exclusivity in socially interactive digital spaces. Maier et al. [7] provided 4 items for social overload, based on recent developments in digital fatigue and information pressure in AI-enabled commerce. Five indicators of consumer engagement were selected from Brodie et al. [28], and emotional resonance and immersion interaction indicators were adopted from Xu and Ruan [3] and Chakraborty et al. [29]. Four items from Gefen et al. [30] were adopted to measure trust and adapted to assess people's perceptions of the reliability and honesty of broadcasters in live-streaming situations. Oliver [17] put forward the three types of satisfaction, and these were adapted to assess how consumers viewed the environment of the interactive AI- and human-led sessions. Impulsive consumption was measured by the four items in Rook and Fisher [31], and recent applications to live-streaming commerce have also been incorporated.

A small-scale trial of 50 people was conducted to assess the clarity and reliability of the items. The Cronbach's alpha coefficients were in the range of 0.79 to 0.88, and therefore met the lower bound of 0.70 proposed by Nunnally and Bernstein [32]. According to the participants' feedback, some modifications were made to improve the fit with the context for the elements involving new concepts of AI interaction. Detailed measurement properties, factor loadings, and adaptation sources are presented in the Appendix (Tables A1–A2).

For each broadcaster condition, item wording was adapted to match the relevant broadcaster type. Items in the AI broadcaster group referred to “AI broadcasters,” whereas the corresponding items in the human broadcaster group referred to “human broadcasters.”

3.4. Data Analysis Strategy

Data analysis was conducted in two stages using SPSS 26 and SmartPLS 4.0. In the first stage, the measurement model was assessed by examining internal consistency reliability (Cronbach's alpha and composite reliability), convergent validity (AVE), and discriminant validity (Fornell-Larcker criterion and HTMT ratios). The second stage was the evaluation of the structural model via partial least squares structural equation modeling (PLS-SEM) with 5,000 bootstrap resamples. This approach enabled the estimation of path coefficients and tests for mediation, as well as explorations for moderation through interaction terms [22, 33]. Groups of each AI and human cohort were compared using MultiGroup and checked for measurement invariance to make valid between-groups comparisons.

Procedural remedies were adopted during questionnaire design, including anonymity assurance, randomized item ordering, and mixed-scale placement. To control for the risk of variance in common-method bias, Harman's single-factor test and collinearity diagnostics were run and showed no strong biases. These procedures provided a systematic basis for evaluating the robustness of the structural relationships among broadcasters, consumer engagement, and impulsive consumption.

4. Results

This section presents the findings from two consumer groups: respondents with experience in AI broadcaster-led live-streaming sessions ($n = 301$) and respondents with experience in human broadcaster-led sessions ($n = 504$). Before hypothesis testing, both datasets were screened for missing values and distributional properties to ensure their suitability for PLS-SEM analysis.

Concerning reliability and validity for both groups, the measurement model was evaluated for all constructs to have acceptable values for all: Cronbach's alpha, CR, AVE, Fornell-Lacker, and HTMT. It is also the case that when these measures appear to be so robust across contexts, from AI to human broadcaster, a comparable basis for analysis is established to measure against [34].

Then, the structural model was analysed to test the hypotheses as stated in the conceptual framework, as calculated: path coefficient (β), t value, significance (p -value), coefficient of determination (R^2), predictive relevance (Q^2). Harman's single-factor test was performed separately for each group to check if common method variance would affect the results [35].

The structural model analysis reveals the effect pathways of AI and human broadcasters on consumer engagement and impulsive buying. With a greater focus placed on the mediating role of perceived status and consumer senses, and the differences it has as social overload moderates the relationship for each broadcaster condition. A systematic presentation of the detailed explanation and breakdown of these findings is presented in the following sub-sections.

4.1. Measurement Model Assessment

As depicted in Table 2, the measurement model demonstrated strong psychometric properties across both AI and human broadcaster conditions. All item factor loadings exceeded the threshold of 0.70, ranging from 0.791 to 0.874, and thus were considered reliable. Cronbach's Alpha (CA) and Composite Reliability (CR) were used to evaluate the internal consistency, and both exceeded the recommended value of 0.70 [32, 36] with values ranging from 0.765 to 0.887 for CA and 0.864 to 0.917 for CR.

All of the constructs showed good convergent validity ($AVE > 0.50$), and the measurement indicators for both the AI and human broadcaster scenarios consistently reflected the intended latent variables [36].

Overall, these psychometric results support the reliability, internal consistency, and convergent validity of the measurement instruments utilized to assess consumer perceptions and behaviors toward AI and human broadcasters, providing confidence in the robustness of the subsequent structural analysis.

Table 2.
Reliability and convergent validity result.

Construct	Type	Items	Loadings Range	Cronbach's Alpha	Composite Reliability	AVE
AIB	AI	AIB1–AIB4	0.812–0.845	0.848	0.898	0.687
HB	Human	HB1–HB3	0.832–0.861	0.802	0.884	0.717
CE	AI	CE1–CE5	0.798–0.829	0.872	0.907	0.661
CE	Human	CE1–CE5	0.813–0.847	0.885	0.916	0.686
CSa	AI	CSa1–CSa3	0.852–0.874	0.823	0.894	0.738
CSa	Human	CSa1–CSa3	0.855–0.872	0.828	0.897	0.744
CSe	AI	CSe1–CSe3	0.823–0.856	0.797	0.881	0.711
CSe	Human	CSe1–CSe3	0.816–0.836	0.765	0.864	0.68
IC	AI	IC1–IC4	0.808–0.863	0.862	0.906	0.708
IC	Human	IC1–IC4	0.807–0.845	0.845	0.896	0.684
PSE	AI	PSE1–PSE5	0.790–0.848	0.873	0.908	0.663
PSE	Human	PSE1–PSE5	0.817–0.842	0.887	0.917	0.688
SO	AI	SO1–SO4	0.791–0.843	0.837	0.89	0.668
SO	Human	SO1–SO4	0.807–0.842	0.852	0.9	0.691
Tru	AI	Tru1–Tru4	0.817–0.858	0.863	0.907	0.709
Tru	Human	Tru1–Tru4	0.821–0.856	0.859	0.904	0.703

Discriminant validity was examined by the Fornell-Larcker criterion with the square root of AVE of all constructs compared to the inter-construct correlation within AI and human broadcaster. It's important to do this analysis to make sure each theoretical measurement was for different phenomena, with no big overlap, especially when comparing live-streaming commerce studies [3].

As summarized in Table 3, the square root of the AVEs (bold on the diagonal) was greater than its respective inter-construct correlations for both the broadcaster groups. Specifically, the square root of AVEs is as follows: 0.813 (AI-CE) and 0.859 (AI-CSa), and 0.825 (Human-CSe) and 0.862 (Human-CSa), all of which are much higher than the off-diagonal correlation value itself, confirming good discriminant validity. This indicates that each construct is unique in its capture of the respective theoretical domain, leading to the next structural model evaluation.

Table 3.
Fornell-Larcker criterion.

Construct	Type	AIB	HB	CE	CSa	CSe	IC	PSE	SO	Tru
AIB	AI	0.829								
HB	Human		0.847							
CE	AI	0.23		0.813						
	Human		0.236	0.828						
CSa	AI	0.287		0.14	0.859					
	Human		0.376	0.303	0.862					
CSe	AI	0.213		0.154	0.324	0.843				
	Human		0.325	0.253	0.386	0.825				
IC	AI	0.39		0.148	0.335	0.242	0.841			
	Human		0.377	0.263	0.365	0.395	0.827			
PSE	AI	0.366		0.244	0.319	0.283	0.449	0.814		
	Human		0.354	0.352	0.357	0.352	0.359	0.829		
SO	AI	0.264		0.159	0.38	0.25	0.389	0.399	0.818	
	Human		0.401	0.266	0.284	0.341	0.387	0.359	0.831	
Tru	AI	0.297		0.173	0.382	0.24	0.382	0.441	0.426	0.842
	Human		0.372	0.331	0.397	0.345	0.314	0.316	0.332	0.838

Moreover, construct discriminant validity was assessed through the Heterotrait–Monotrait (HTMT) criterion, a standard widely adopted by recent empirical literature for its sensitivity and accuracy in distinguishing construct validity [34]. If the HTMT values were below the recommended maximum of 0.85, then it would imply that the construct boundaries were clear.

According to Table 4, both groups of AI broadcaster and Human broadcaster HTMT analysis showed positive outcomes, with all pairwise correlation values lower than the critical value. Specifically, HTMT values ranged from 0.029 (between AI broadcaster interactions and consumer engagement under social overload moderation) to 0.514 (AI broadcasters' perceived status elevation and impulsive consumption). Similarly, within the Human broadcaster condition, HTMT results varied from 0.013 (interaction of social overload with consumer senses and consumer senses directly) to 0.489 (between Consumer senses and impulsive consumption).

A stable appearance of HTMT values below the recommended limit provides full support for the discriminant validity of the employed constructs and guarantees the reliability of subsequent hypothesis testing and structural model interpretation.

Table 4.
HTMT criterion.

Construct	Type	AIB	CE	CSa	CSe	IC	PSE	SO	Tru	SO × AIB	SO × CSe
AIB	AI		0.267	0.345	0.259	0.456	0.423	0.316	0.35	0.073	0.102
HB	Human		0.279	0.46	0.412	0.46	0.417	0.482	0.449	0.234	0.078
CE	AI			0.162	0.186	0.169	0.279	0.182	0.199	0.029	0.087
CE	Human			0.351	0.307	0.303	0.395	0.304	0.379	0.082	0.069
CSa	AI				0.399	0.395	0.374	0.457	0.45	0.103	0.155
CSa	Human				0.484	0.435	0.413	0.334	0.472	0.078	0.05
CSe	AI					0.289	0.338	0.295	0.288	0.106	0.034
CSe	Human					0.489	0.427	0.419	0.426	0.013	0.143
IC	AI						0.514	0.455	0.439	0.065	0.087
IC	Human						0.415	0.454	0.367	0.029	0.025
PSE	AI							0.468	0.506	0.066	0.054
PSE	Human							0.408	0.362	0.043	0.027
SO	AI								0.497	0.046	0.053
SO	Human								0.383	0.226	0.165
Tru	AI									0.044	0.085
Tru	Human									0.055	0.043

Harman's single-factor test was used to determine whether there was a problem of common method bias systematically via exploratory factor analysis (EFA) in SPSS 26, according to the suggestions put forward by Podsakoff et al. [35]. As shown in Table 5, several factors were identified with eigenvalues greater than 1 for both the AI and human broadcaster groups, and together they accounted for a significant proportion of the total variance (69.76%).

The first factor accounted for only 27.28% of the variance in the AI broadcaster group and 29.40% in the Human broadcaster group, both of which were significantly lower than the typical 50% threshold for a common method bias [35]. Based on the above results, the findings indicate that common method bias was not a significant issue in this study and will not affect the accuracy and validity of the following hypothesis tests and structural analyses.

Table 5.
Total Variance Explained.

Component	Group	Initial Eigenvalue	% of Variance	Cumulative %
1	AI	8.728	27.276	27.276
	Human	9.113	29.397	29.397
2	AI	3.041	9.502	36.778
	Human	2.621	8.455	37.852
3	AI	2.161	6.754	43.532
	Human	2.208	7.124	44.976
4	AI	1.962	6.13	49.663
	Human	1.943	6.267	51.242
5	AI	1.813	5.665	55.328
	Human	1.796	5.793	57.036
6	AI	1.694	5.295	60.623
	Human	1.454	4.69	61.726
7	AI	1.551	4.848	65.471
	Human	1.417	4.571	66.297
8	AI	1.372	4.286	69.757
	Human	1.24	4	70.297

4.2. Structural Model Assessment

4.2.1. Direct Effects

To explore the expected connections among these factors, bootstrapping with 5000 subdivisions was employed to evaluate the structural model in line with the good practices proposed by Hair [37] and Henseler et al. [34]. Table 6 shows the results of hypothesis testing for the paths of AI and human broadcasters.

Based on the above analysis, AI broadcasters positively promoted the perception of status ($\beta = 0.366$, $t = 7.814$, $p < 0.001$), and thus supported H1. Human broadcasters also had a significant positive effect on PSE ($\beta = 0.354$, $t = 8.835$, $p < 0.001$) and thus supported H2. In addition, human broadcasters also significantly affected Consumer senses (CSe) ($\beta = 0.240$, $t = 5.564$, $p < 0.001$), confirming H3, and AI broadcasters also had a significant, though smaller, impact on CSe ($\beta = 0.150$, $t = 3.106$, $p = 0.001$), validating H4.

Perceived status elevation positively predicted consumer satisfaction for both AI ($\beta = 0.319$, $t = 7.038$, $p < 0.001$) and human broadcasters ($\beta = 0.357$, $t = 8.819$, $p < 0.001$), and thus H7 was supported in both cases.

Consumer senses are positively correlated with both forms of consumer engagement. For AI broadcasters, the effect was modest yet significant ($\beta = 0.107$, $t = 1.953$, $p = 0.025$), and for human broadcasters, the relationship was stronger ($\beta = 0.126$, $t = 2.496$, $p = 0.006$), validating H9.

Consumer engagement significantly predicted trust in both groups. The effect was positive and significant for the AI broadcaster group ($\beta = 0.174$, $t = 3.756$, $p < 0.001$) and stronger for the human broadcaster group ($\beta = 0.331$, $t = 7.605$, $p < 0.001$), supporting H10 in both contexts. This suggests that engagement contributes to trust formation in both AI- and human-led live-streaming commerce, although the effect is stronger in human-led interactions. Consumer satisfaction only showed a significant positive effect on consumer engagement in the human group ($\beta = 0.200$, $t = 3.963$, $p < 0.001$), but was not statistically significant for the AI group ($\beta = 0.051$, $t = 0.870$, $p = 0.192$); thus, it provided partial support for H11.

For impulsive consumption (IC), trust had a significant impact in both conditions (AI: $\beta = 0.281$, $t = 5.602$, $p < 0.001$; Human: $\beta = 0.169$, $t = 3.546$, $p < 0.001$), confirming H12. Consumer satisfaction also significantly influenced IC (AI: $\beta = 0.223$, $t = 4.517$, $p < 0.001$; Human: $\beta = 0.259$, $t = 5.169$, $p < 0.001$), supporting H13. Finally, only in the human broadcaster scenario was consumer engagement

significantly positively related to IC ($\beta = 0.129$, $t = 2.698$, $p = 0.004$), but not in the AI context ($\beta = 0.063$, $t = 1.390$, $p = 0.082$), thus only partially supporting H14.

Table 6.
Hypothesis Testing Results.

(Includes β values, standard errors, t-values, and p-values)						
Hypothesis	Path	Type	β (Path Coefficient)	t-value	p-value	Support
H1	AIB $\rightarrow$ PSE	AI	0.366	7.814	<0.001	S
H2	HB $\rightarrow$ PSE	Human	0.354	8.835	<0.001	S
H3	HB $\rightarrow$ CSe	Human	0.24	5.564	<0.001	S
H4	AIB $\rightarrow$ CSe	AI	0.15	3.106	0.001	S
H7	PSE $\rightarrow$ CSa	AI	0.319	7.038	<0.001	S
H7	PSE $\rightarrow$ CSa	Human	0.357	8.819	<0.001	S
H9	CSe $\rightarrow$ CE	AI	0.107	1.953	0.025	S
H9	CSe $\rightarrow$ CE	Human	0.126	2.496	0.006	S
H10	CE $\rightarrow$ Tru	AI	0.174	3.756	<0.001	S
H10	CE $\rightarrow$ Tru	Human	0.331	7.605	<0.001	S
H11	CSa $\rightarrow$ CE	AI	0.051	0.87	0.192	NS
H11	CSa $\rightarrow$ CE	Human	0.2	3.963	<0.001	S
H12	Tru $\rightarrow$ IC	AI	0.281	5.602	<0.001	S
H12	Tru $\rightarrow$ IC	Human	0.169	3.546	<0.001	S
H13	CSa $\rightarrow$ IC	AI	0.223	4.517	<0.001	S
H13	CSa $\rightarrow$ IC	Human	0.259	5.169	<0.001	S
H14	CE $\rightarrow$ IC	AI	0.063	1.39	0.082	NS
H14	CE $\rightarrow$ IC	Human	0.129	2.698	0.004	S

Table 7.
 R^2 and Q^2 Values for the Structural Model.

	Type	R-square	Q^2 (=1-SSE/SSO)
CE	AIB	0.032	0.019
	HB	0.146	
CSa	AIB	0.102	0.073
	HB	0.127	
CSe	AIB	0.046	0.031
	HB	0.17	
IC	AIB	0.19	0.137
	HB	0.182	
PSE	AIB	0.134	0.085
	HB	0.125	
Tru	AIB	0.03	0.018
	HB	0.109	

4.2.2. Moderating Effects

Hair [37] put forward the above ways to conduct bootstrap resampling for the analysis of moderator effects. Table 8 shows the particular results of the hypothesized moderating effects of social overload (SO) in the contexts of AI and human broadcasters.

The interaction of social overload and AI broadcasters on Consumer senses (SO $\times$ AIB $\rightarrow$ CSe) was statistically significant for the AI broadcaster group (AIB), with a regression coefficient of 0.099, a 95% confidence interval of [0.027, 0.17], and a p-value of 0.012; thus, supporting H6. Based on the above, it can be seen that under conditions of elevated social overload, consumers tend to respond more favorably to the organised and regular broadcasts of AI broadcasters. Based on the above studies, it can be assumed that a higher demand for low-effort, technology-mediated communication channels among consumers may arise under conditions of overload [7].

Similarly, in the human broadcaster group (HB), the interaction effect of social overload and human broadcasters on consumer senses was statistically significant and positive ($\beta = 0.104$, 95% CI $[-0.046, 0.169]$, $p = 0.006$), supporting H5. This finding indicates that social overload strengthens the relationship between human broadcasters and consumer senses.

For the AI broadcaster context, the moderating effect of social overload on the relationship between Consumer senses and consumer engagement was not statistically significant ($\beta = 0.080$, 95% CI $[-0.015, 0.161]$, $p = 0.069$), indicating that H8 was not supported in the AI group. In contrast, this interaction was significant in the human broadcaster group ($\beta = 0.095$, $t = 2.446$, 95% CI $[-0.024, 0.156]$, $p = 0.007$), supporting H8 for human-led streams. Therefore, H8 was partially supported. This result shows that, in the presence of social overstimulation, human-driven streams are more likely to turn increased sensory input into active engagement; such a pattern has been observed in the literature on live-streaming social interaction [7].

Collectively, the above results indicate that the impact of social overload is context-dependent and may affect the structure of human-led streams differently from that of AI-led streams.

Table 8.

Assessment of moderating effects.

Hyp	Type	Path	β (Path Coefficient)	95%CI	P values	Results
H6	AIB	SO x AIB -> CSe	0.099	0.027-0.17	0.012	S
H5	HB	SO x HB -> CSe	0.104	0.046-0.169	0.006	S
H8	AIB	SO x CSe -> CE	0.08	-0.015-0.161	0.069	NS
H8	HB	SO x CSe -> CE	0.095	0.024-0.156	0.007	S

4.2.3. Indirect Effects

To further explore the psychological mechanisms by which AI and human broadcasters, as well as social overload, affect consumer engagement and impulsive consumption, a series of comprehensive indirect paths within the S-O-R framework have been tested in this study. As shown in Table 9, some relatively large indirect effects were found after mediation analysis.

Among respondents exposed to AI broadcasters, social overload was positively associated with consumer engagement through Consumer senses (SO $\rightarrow$ CSe $\rightarrow$ CE: $\beta = 0.100$, $t = 3.686$, $p < 0.001$), and this result is consistent with prior research that has shown that social or cognitive stress increases a person's need for highly stimulating sensory input in consuming media [7, 38]. Similarly, the mediation effect for human broadcasters was also relatively small but still statistically significant ($\beta = 0.034$, $t = 2.207$, $p = 0.014$).

Both AI and human broadcasters influenced impulsive consumption through the sequential pathway of status elevation and consumer satisfaction (AI: $\beta = 0.040$, $t = 3.036$, $p = 0.001$; Human: $\beta = 0.033$, $t = 3.258$, $p = 0.001$), highlighting the emotional and symbolic recognition offered by both types of broadcasters.

Several more complex mediation chains were also substantiated. For instance, social overload was shown to drive impulsive consumption through both engagement and trust (AI: SO $\rightarrow$ CE $\rightarrow$ Tru $\rightarrow$ IC, $\beta = 0.015$, $t = 2.274$, $p = 0.012$; Human: $\beta = 0.01$, $t = 2.264$, $p = 0.012$), and also via the full sequential route of SO $\rightarrow$ CSe $\rightarrow$ CE $\rightarrow$ Tru $\rightarrow$ IC (AI: $\beta = 0.008$, $t = 2.284$, $p = 0.011$; Human: $\beta = 0.002$, $t = 1.757$, $p = 0.040$).

Finally, the effect of AI broadcasters on engagement was also realized indirectly through consumer senses (AI: $\beta = 0.089$, $t = 3.115$, $p = 0.001$), further emphasizing the importance of immersive, affect-driven stimuli in activating user involvement [39].

In short, all these findings show the important role of both symbolic and affective organismic states as a mediating role in terms of consumer trust and consumer behavior in livestream commerce. The results lend support to using S-O-R to explain the different levels of psychological processes occurring within AI- and human-mediated digital interaction.

Table 9.
Structural model results for indirect effect.

	Path	β (Path Coefficient)	t-value	P values	Support
AI	SO -> CSe -> CE	0.1	3.686	<0.001	
HB	SO -> CSe -> CE	0.034	2.207	0.014	S
AI	CSe -> CE -> IC	0.119	4.655	<0.001	S
HB	CSe -> CE -> IC	0.016	1.585	0.056	N
AI	AIB -> PSE -> CSa -> IC	0.04	3.036	0.001	S
HB	HB -> PSE -> CSa -> IC	0.033	3.258	0.001	S
AI	CSe -> CE -> Tru	0.113	4.009	<0.001	S
HB	CSe -> CE -> Tru	0.042	2.262	0.012	S
AI	SO -> CE -> IC	0.055	2.413	0.008	S
HB	SO -> CE -> IC	0.023	2.056	0.02	S
AI	SO -> CE -> Tru -> IC	0.015	2.274	0.012	S
HB	SO -> CE -> Tru -> IC	0.01	2.264	0.012	S
AI	SO -> CSe -> CE -> Tru -> IC	0.008	2.284	0.011	S
HB	SO -> CSe -> CE -> Tru -> IC	0.002	1.757	0.04	S
AI	AIB -> CSe -> CE -> Tru -> IC	0.007	2.256	0.012	S
HB	HB -> CSe -> CE -> Tru -> IC	0.002	1.691	0.045	S
AI	SO -> CSe -> CE -> IC	0.029	3.058	0.001	S
HB	SO -> CSe -> CE -> IC	0.004	1.48	0.07	N
AI	AIB -> CSe -> CE	0.089	3.115	0.001	S
HB	HB -> CSe -> CE	0.03	2.105	0.018	S

5. Discussions and Conclusions

Drawing upon the S-O-R model, this study examined how AI and human broadcasters influence consumer engagement and impulsive consumption behaviour in livestream commerce. With the sample of 301 for the AI broadcaster group and also with that of 504 for the human broadcaster group, a substantial comparison was conducted to get detailed descriptions of how the AI broadcasters and the human broadcasters, respectively, work upon the consumers to affect their thoughts.

Empirical findings offer partial backing for viewing both AI and human broadcasters as key external forces in the S-O-R model, influencing crucial organismic activities such as status elevating and sensuality. Even though AI broadcasters give consumers a prestigious experience, people are more multimodal, more consistent with the cues, more interactive, and more spontaneous. AI broadcasters positively influence multisensory engagement, though to a lesser degree than human broadcasters, but slightly less than the average human in the present data [6, 13]. The analysis focused on how broadcaster format influences consumer satisfaction, trust, and impulsive shopping. When AI presentations possess personal and proprietary elements, they make consumers feel unique and give them greater symbolic value and social identity online [40].

Also, data show that interacting with an AI broadcaster with custom interactions increases satisfaction, similar to the data from the virtual retail literature on personal service and special treatment [6, 29]. But if perceived status elevation raises satisfaction, sensing leads to participation directly. The result indicates that immersive affective stimuli are more immediate and more impactful in behavior than cognitive satisfaction in generating active engagement [14, 41].

Findings show that emotional engagement can be reliably linked to an increase in trust, with previous research showing this for digital interaction [30]. Satisfaction and trust constitute the primary drivers of impulsive buying. Engagement leads to immediate purchase decisions among human broadcaster audiences but not among AI broadcaster audiences, showing the impact of affective and relational bases for conversion from involvement into action [31, 42]. These findings illuminate the layered psychological mechanisms underlying live-streaming shopping and underscore the dual necessity to adapt to emerging trends and maintain reliance on established mechanisms.

The moderating results further show that social overload does not uniformly weaken consumer responses in live-streaming commerce. The results are contrary to previous views that social or

cognitive overload is always harmful, in that higher social overload leads to stronger effects of both AI and human broadcasters on consumer senses. The translation from consumer senses to consumer engagement is moderated only by social overload in the human cohort, but it is not a moderated relation in the AI cohort, as indicated by Gao and Zhao [38]. In this particular case, these findings support H5 by showing that social overload strengthens the relationship between human broadcasters and consumer senses; these findings establish boundary conditions on when humans can also be used as an expressive organizing cue within overloaded contexts [14, 41].

Mediation analyses support that the influence of AI broadcasters on impulsive consumption is transmitted through sequential organismic states, such as status elevation, satisfaction, and trust, confirming the layered psychological mechanisms that underpin spontaneous purchase behaviors in live-streaming commerce [39]. Based on the above analysis, it is proposed that future digital marketing strategies should employ rich sensory stimulation, personalised status-enhancing interactions, and trust-building designs, along with clear communication and emotionally intelligent dialogue [30]. At the same time, platform designers need to prevent user fatigue by regulating the intensity of engagement, and excessive amounts of information or prompts will no longer appeal to consumers [38].

Nevertheless, the scope of this study is limited to Chinese consumers, so it may not be generalisable to other cultures or technological conditions [39]. In the future, research will investigate differences among countries, adopt a long-term study method to observe changes in trust and impulsive behaviour over time, and add individual-level moderators, such as digital literacy and AI readiness, to explore how different individuals respond to AI broadcasters in global e-commerce.

6. Theoretical Contributions

This paper greatly expands on the theoretical application of the Stimulus–Organism–Response (S–O–R) model in live-streaming commerce with a direct comparison between AI and human broadcasters. The study shows how these two kinds of stimuli are outlined in contrast with each other through this way of presentation, and artificial intelligence-based interactions can now cause such organismic responses as being seen as having some kind of prestige, getting immersed in doing something, etc., which was previously confined only to human agents [3, 13]. This direct comparative framework yields fresh contributions over simply extending the S–O–R framework into digital commerce since it identifies not only unique things in every sort of broadcaster; human broadcasters frequently have many more multi-sensory reactions on average, though AI advantages occur from regularity and personalized responses, and greater social overload.

Notably, this study shows that both AI and human broadcasters contribute to a feeling of perceived status, but the former do so through algorithmic personalization and the creation of simulated exclusivity, means far removed from the interpersonal status signals thought to be necessary for status signaling [6, 40]. This means that symbolic value and social recognition are no longer reserved for human-run service in digital commerce; artificial intelligence is creating new avenues to display their status.

The study is adding to the social overload by showing that an increase in social or conscious overload does not simply push consumers away but creates more desire from consumers to have more structured and predictable interactions with both human and AI broadcasters [38]. It also complicates the previous view: sometimes, on the issue of information sufficiency, the algorithmic pattern is actually a benefit to cognition, rather than a heavy cognitive load.

Another theoretical concept is an explanation of if engagement and trust would fit into something more about how AI interaction and impulse buying. When the prior research treats them as varied results [28, 29], the results show that a fully engaging sensory experience engenders trust, which in turn triggers impulsive buying behavior, especially in live-streaming commerce scenarios [14, 41].

Drawing upon the S–O–R approach, which encompasses consumer senses, perceived status elevation, satisfaction, and trust, this framework offers a granular understanding of how every type of broadcaster

controls people's emotions. A multi-layer process that will clear up the sequential and interactive organismic processes behind digital consumption [40, 43]. As for the future theory to be considered, it is hoped, in view of the possibility of more human-like AI broadcast presenters, that it shall expand its horizons to include their ability to foster social connection and companionship in society through digital media, thereby integrating transactionality and affective consumer outcome [14, 44].

7. Practical Implications

The findings of this study can be used to provide practical instructions to marketers as well as to e-commerce platforms that would like to make the most out of the unique features of AI broadcasters in the live-streaming commerce world. Digital retail is going through a change; properly setting up AI agents may not just make consumers more involved, but could also gain their trust and encourage them to buy more things unexpectedly in busier markets. The results indicate that advanced AI avatars with anthropomorphism and interactive responses can be utilised to heighten sensory input, especially in cases of high social overload and where consistency and customisation are necessary, and thereby focus consumer attention. The findings suggest that trust and satisfaction are consistent predictors of impulsive consumption across both broadcaster types, whereas consumer engagement translates into impulsive consumption mainly in the human broadcaster context [13, 41]. Therefore, AI broadcasters should be designed with expressive hand gestures, fluid conversations, and modulated voices that approximate human expressiveness, thereby reducing perceived emotional distance on digital platforms.

Consumer senses can act as a psychological trigger for impulsivity, but it might be different if it were an AI-driven or a human stimulus. Dynamic visuals, immersion storytelling, and emotional narrative could contribute substantially to experiential pleasure [14, 29], but AI-empowered commerce makes the personalized services more on target and provides instant feedback with varied senses like sounds and moving pictures, contrast-changing texts, and definite emotions from human hosts.

To maintain positive interactions continuously, platforms should manage social overload effectively. And after the users use the AI and human-triggered stream too many times, they will be bored [38]. AI systems can mitigate fatigue by moderating interaction frequency and pacing. Platforms must make use of these choices that are changeable and have to tweak the amount of their participation so that it is not too overwhelming but will be satisfying and agreeable.

From the same data, they also see that personalization, such as just reinforcing status with AI to scale and get VIP access, recognition, personalization, all that other stuff that wasn't possible before [6, 40]. Unlike humans, who are hosts, AI can also slice and respond to people's profiles in real time, and this means platforms can build loyalty to each consumer individually and to different segments of those consumers separately.

Building and securing consumer trust holds importance for both AI-driven and human-mediated live commerce, but the mechanisms through which this is achieved vary considerably. Regarding AI-mediated contexts, platforms should transcend traditional safeguards through the application of real-time analytics to gauge user sentiment, provide visible labeling for AI content, and automate product claims' validity checks [3, 30]. AI agents, unlike human broadcasters whose trust derives from the notion of 'being real' or the feeling of personal warmth, will have to make a conscious and systematic effort towards reducing the uncertainty through explicit disclosures, speedy feedback, and solving users' doubts before these questions arise. The combination of these mechanisms into the platform not only reduces the perceived risk but also the gap between the degree of engagement and the decision to make a purchase [29].

In operations, one major strength of AI broadcasters compared to human broadcasters is the possibility of real-time audience segmentation and delivery. The platforms utilize machine learning for their analysis of users' information like the movies they watch, their purchasing history, and how they relate to various movie genres, and adjust their content, style, and ways to engage with them in real time [39]. Take the AI broadcasting idea, for example: right away adjusting the tone and incentive for different age groups, or even shopping styles, giving something fun as a reward to the digital natives,

then adding an explanation for those who aren't always on top of the newest piece of gear or whatever. This level of personalized interaction is impossible to replicate on a scale without human hosts, yet it has also raised customer retention and higher conversion.

And in the end, AI broadcasters can be part of all the different channels, which allows brands to give customers an experience of themselves, and over many different touch points and experiences. Just like people streamers, AI figures have a hard time managing different messaging and the scale of different platforms, but they can serve as digital brand representatives, and they can keep their same messages, styles, and even sales for both real-world events and virtual stores, social media channels. When these AI versions show the vibes and values of the brand, it makes people feel warm and good at the same time, so it also adds up to making the brand have more worth later on [44].

This evidence-based knowledge enables researchers to effectively deploy AI broadcasters in dynamic commercial environments.

8. Limitations and Future Research Directions

Although this paper would likely offer good evidence to determine how an AI broadcaster vs a human broadcaster affects consumer engagement and impulse purchases, there are a few issues. The cross-sectional design captures only a single temporal snapshot, so the authors cannot ascertain a lot about how the findings are causally connected in a cause-and-effect way between different broadcaster types, people's ideas, and what they do. Although more complex checks can be conducted on what happens together in Structural Equation Modeling, it does not show how trust, involvement, or the urge to buy change as people encounter AI over time. In future research, longitudinal or panel data might be used to examine how psychological and behavioral reactions develop across several digital appearances [45].

Another restriction is that all the respondents were Chinese consumers in the sample. Cultural tendencies towards technology acceptance, collectivism, and digital engagement styles may be different from those in more individualistic or heterogeneous societies, and thus the generalizability of the findings may be limited [40]. Therefore, in the future, various studies will be conducted in different cultural and regulatory environments to investigate how local norms, technological readiness, and privacy attitudes affect AI-mediated consumer engagement.

A single method of self-reported survey responses may be subject to common-method bias and social desirability bias. Although the results of Harman's single-factor test are not serious, further research needs to be conducted to triangulate the survey data with behavioural analysis and other types of information sources, and to obtain an all-around understanding of people's conscious and unconscious responses to AI, as well as to reduce the limitation of subjectivity in evaluation [29].

Although the current model has included several important states of the organism, such as status elevation, satisfaction, and trust, not all factors that can influence people's attitudes toward the brand have been taken into account. Tech anxiety, novelty-seeking tendencies, and self-discipline are all subjects worthy of study in terms of how open people are to changes in their way of thinking and feeling under the influence of AI [2, 14]. Future work can look at these moderators to contribute to creating even more adaptable and bespoke AI conversations.

In this study, social overload was operationalised as perceived pressure arising from excessive social and informational demands in live-streaming commerce. However, bigger facets of being tired from the digital were not considered, like concerns regarding data privacy, if computers are tricking people, and believing that they are being surveilled online. As people become more aware of how much personalization and surveillance AI does, people might get more resistant or doubtful about it, which could have a big effect on how they act or believe about it [38].

Lastly, this study did not include any contextual-level or product-level moderator, such as product category, consumer involvement, or realism of the AI avatar. Different product domains, such as hedonic vs. utilitarian, and levels of avatar realism, can lead to different consumer responses to a robot

broadcaster vs. a human broadcaster [6]. Future studies could look into those surrounding effects so as to improve the accuracy and strength of AIs in different live-streaming situations.

To solve these problems for other types of participants and explore them with different methods, it will be necessary in order to discover new facets of psychology, as well as new context variables, to advance both theory around AI-fueled engagement in live streaming commerce and its practical application.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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Appendix

Table A1.

Measurement items and sources.

Construct	Items	Source
AI Broadcaster Characteristics (AIB)	AIB 1: I think the AI broadcaster acted with a clear intention.	Sun and Tang [46]
	AIB 2: I believe the AI broadcaster demonstrated real emotions.	Sun and Tang [46]
	AIB 3: The AI broadcaster appeared to make decisions independently.	Sun and Tang [46]
	AIB 4: I felt the AI broadcaster was aware and responsive.	Sun and Tang [46]
Human Broadcaster (HB)	HB1: The human broadcaster interacted with viewers naturally and responsively.	Hossain, et al. [47]
	HB2: The human broadcaster appeared authentic and emotionally expressive during the live-streaming session.	Hossain, et al. [47]
	HB3: The human broadcaster provided clear and engaging product information during the live-streaming session.	Hossain, et al. [47]
Trust (Tru)	Tru 1: I trust that the products I receive will be the same as those demonstrated by the AI broadcaster.	Wang, et al. [48]
	Tru 2: I trust that AI broadcasters in live streaming are reliable and prioritize the interests of consumers.	Guo, et al. [49]
	Tru 3: The AI broadcaster is trustworthy.	Guo, et al. [49]
	Tru 4: The AI broadcaster is reliable.	Guo, et al. [49]
Social Overload (SO)	SO 1: I care too much for others on social media platforms.	Xu and Ruan [3]
	SO 2: I deal too much with others' problems on social	Xu and Ruan [3]

	media platforms.	
	SO 3: I take too much care of others' well-being on social media platforms.	Xu and Ruan [3]
	SO 4: I spend too much time following content shared by AI broadcasters in live streaming.	Li, et al. [39]
Perceived Status Elevation (PSE)	PSE 1: The AI broadcaster's personalized content makes me feel special.	Choi, et al. [6]
	PSE 2: I would choose a particular product recommended by the AI broadcaster because it has prestige.	Gao and Zhao [38]
	PSE 3: The status of a product recommended by the AI broadcaster is important to me	Gao and Zhao [38]
	PSE 4: I would pay for a product if the AI broadcaster highlights its sense of fame.	Gao and Zhao [38]
	PSE 5: A product is significant to me if it has a luxurious or exclusive appeal as presented by the AI broadcaster.	Gao and Zhao [38]
Consumer Senses (CSe)	CSe 1: I feel pleased while watching live streaming hosted by AI broadcasters.	Xu and Ruan [3]
	CSe 2: When I watch live streaming hosted by AI broadcasters, I feel very excited.	Xu and Ruan [3]
	CSe 3: The dynamic and engaging content delivered by AI broadcasters intrigues me.	Li, et al. [39]
Consumer Engagement (CE)	CE 1: I would interact with the AI broadcaster and other viewers during live streaming.	Xu and Ruan [3]
	CE 2: I feel engaged while watching virtual live shopping platforms hosted by AI broadcasters.	Sun and Tang [46]
	CE 3: The virtual live shopping platform experience with AI broadcasters captures my full attention.	Sun and Tang [46]
	CE 4: I look for ideas or information from others during AI broadcaster-led live streaming sessions.	Luo, et al. [5]
	CE 5: I am likely to recommend AI broadcasters who use live streaming to my friends.	Luo, et al. [5]
Consumer Satisfaction(CSa)	CSa 1: I am satisfied with the product selection recommended by AI broadcasters.	Goel, et al. [50]
	CSa 2: I am satisfied with the quality of the products recommended by AI broadcasters.	Goel, et al. [50]
	CSa 3: I am satisfied with the service and content delivered by AI broadcasters.	Choi, et al. [6]
Impulsive Consumption (IC)	IC 1: I sometimes buy products impulsively during AI broadcaster live streams without thorough consideration.	Li, et al. [39]
	IC 2: I tend to make purchases without prior planning during AI broadcaster live streaming sessions.	Luo, et al. [5]
	IC 3: I have made purchases based on the AI broadcaster's presentation, realizing an immediate need.	Li, et al. [39]
	IC 4: I frequently make purchases without giving them much thought during AI broadcaster live streaming.	Li, et al. [39]

Table A2a.
Demographic profile of the AI broadcaster group (N=301).

Demographics	Number of respondents (N=301)	Percentage (%)
Times		
0 times	17	5.60%
1-9 times	123	40.90%
10-19 times	86	28.60%
20-39 times	41	13.60%
More than 40 times	34	11.30%
Gender		
Male	165	54.80%
Female	136	45.20%
Age		
18-24 years	123	40.90%
25-34 years	85	28.20%
35-44 years	54	17.90%
45-54 years	39	13.00%
55 years or older	0	0.00%
Income		
Below 3,999	52	17.30%
4,000- 6,999	85	28.20%
7,000- 9,999	100	33.20%
10,000-14,999	37	12.30%
Above 15,000	27	9.00%
Consumption Level		
Less than 499	85	28.20%
□ 500- 999	118	39.20%
□ 1,000-1,999	56	18.60%
□ 2,000- 3,999	27	9.00%
□ 4,000 or more	15	5.00%
Like		
AI Broadcasters (e.g., virtual influencers, automated hosts)	96	31.90%
Human Broadcasters (real-person hosts with live interaction)	136	45.20%
No preference	69	22.90%

Table A2b.
Demographic profile of the human broadcaster group (N=504).

Demographics	Number of respondents (N=504)	Percentage (%)
Times		
0 times	0	0.00%
1-9 times	44	8.70%
10-19 times	90	17.90%
20-39 times	150	29.80%
More than 40 times	220	43.70%
Gender		
Male	191	37.90%
Female	313	62.10%
Age		
18-30 years	185	36.70%
31-40 years	138	27.40%
41-50 years	94	18.70%
51 years or older	87	17.30%
Income		
Below 3,999	56	11.10%

4,000– 6,999	109	21.60%
7,000– 9,999	160	31.70%
10,000–14,999	87	17.30%
Above 15,000	92	18.30%
Consumption Level		
Less than 499	60	11.90%
□ 500– 999	64	12.70%
□ 1,000–1,999	132	26.20%
□ 2,000– 3,999	149	29.60%
□ 4,000 or more	99	19.60%
Like		
Human Broadcasters (real-person hosts with live interaction)	287	56.90%
AI Broadcasters (e.g., virtual influencers, automated hosts)	142	28.20%
No preference	75	14.90%