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PAPER

Designing Persuasive Mobile Live-Commerce Systems: An ELM–SOR Analysis of Interactive Interface Cues and Consumer Engagement

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ABSTRACT

Mobile live-streaming commerce has quickly changed digital shopping. It lets people interact in real time, see products in different ways, and connect with others through mobile apps. Even though many use these platforms, keeping users engaged remains a major challenge for designers and retailers. This study uses the elaboration likelihood model (ELM) and the stimulus–organism–response (SOR) framework to examine how interactive mobile interface cues affect customer engagement and purchase behaviour in mobile live-commerce settings. This study examined six interface stimuli: product information quality, streamer interaction quality, streamer credibility, bullet-screen consistency, monetary incentives, and popularity cues. Susceptibility to informational influence (SII) was included as a moderating factor. Data came from 500 Chinese Millennial mobile live-streaming shoppers and were analysed using partial least squares structural equation modelling (PLS-SEM). The findings show that all six interface cues help increase customer engagement. Streamer interaction quality and product information quality have the biggest impact. Customer engagement strongly predicts purchase intention and completely mediates the link between each interface cue and purchase intention. Furthermore, SII significantly amplifies the effects of streamer credibility, bullet-screen consistency, and popularity cues on user engagement but does not moderate the effects of information quality, interaction quality, or monetary incentives. These findings advance mobile human-computer interaction (HCI) research by elucidating how interactive interface features influence user engagement and by offering practical guidance for designing more engaging and personalised mobile live-commerce applications.

KEYWORDS

mobile live-commerce, interactive mobile interfaces, customer engagement, purchase intention, elaboration likelihood model (ELM), stimulus–organism–response (SOR)

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1 INTRODUCTION

Advance development and evolution in mobile operating systems and high-speed internet have opened an era of immersive digital shopping ecosystems, with mobile live-streaming commerce (LSC) emerging as a transformative architectural innovation [1–2]. Unlike conventional text-based or static image product presentations, LSC integrates real-time video, audio, and interactive features, enabling sellers to engage consumers through live demonstrations and instantaneous communication [3]. The experiential consumption model is now popular worldwide. In the United States, LSC brought in $50 billion in revenue in 2023 and is expected to reach $55 billion by 2026 [4]. China leads the global market, with its LSC sector valued at about $423 billion and supported by 526 million active users. These users make up 48.8% of China's total internet population [4]. Most LSC consumers are young, with millennials accounting for nearly 80% of the market [5]. Despite rapid growth, many streamers still struggle to earn a sustainable profit. In China, about 1.23 million streamers reportedly do not achieve profitable results, because of this, learning to communicate persuasive messages that boost consumer engagement and purchase intent remains a major challenge for the LSC industry [6].

The elaboration likelihood model (ELM) is a useful framework for understanding how persuasion works in LSC [7]. In LSC, the central route occurs when consumers carefully consider key factors, such as the quality of product information or the streamer's expertise. The peripheral route, on the other hand, depends on quick cues or emotional reactions, such as the streamer's appearance, humour, or interactions with other viewers, to shape trust and prompt quick purchases [8].

Traditional e-commerce factors are usually quality of product information. Peripheral cues are source attractiveness and consensus signals. However, LSC implements additional aspects of real-time host–audience interaction, changing monetary incentive systems, and new variable selections and theory specifications [9]. The host (streamer) is the major information bearer, and the quality of the interaction between the host and the viewers is a crucial central route factor, and the quality of information content is not adequate [2].

Although all these developments have been made, there remain many research gaps. First, the use of ELM in LSC is still very little developed, especially in terms of integration of host-related persuasive factors. Second, the stimulus-Organism-response (SOR) paradigm needs to be continually updated to include new LSC-specific stimuli, including a real-time popularity indicator. Third, consumers' susceptibility to informational influence (SII), one key individual difference variable that influences the processing of persuasive messages, has not received much attention in the context of LSC [10]. This study investigates how informational susceptibility moderates the relationship between persuasive information factors—such as product information quality, streamer interaction quality, streamer credibility, monetary incentives, bullet-screen consistency, and popularity cues—and purchase intention among Chinese Millennial live-stream commerce users. In doing so, it addresses existing research gaps.

2 LITERATURE REVIEW

2.1 ELM

The ELM was developed by Petty and Cacioppo [11] and describes how persuasive communication leads to attitude change via two different routes. The "core path" is the route requiring great desire and cognitive effort to process the quality and content of the argument. In contrast, the "peripheral route" uses simple heuristics, emotional cues, or superficial features such as source beauty. Whether a person takes the central or peripheral path depends totally on their motivation and capacity to digest the information [12]. Recently, ELM has attracted much attention in LSC research, since the unique environment of LSC integrates rich real-time data with many heuristic cues.

2.2 SOR framework

The SOR model, from environmental psychology can be used to analyse the environmental stimuli that induce internal affective and cognitive responses (the organism) that subsequently lead to behavioural responses of the users. The SOR model is widely used to describe the relationship between the stimuli, the organism (emotional and cognitive responses) and the behavioural responses (approach or avoidance) in e-commerce research [13]. The SOR framework in this study is combined with ELM to model the entire persuasive information processing process in LSC. Specifically, the stimuli (S) consist of persuasive information factors related to ELM from both central and peripheral routes, such as product information quality (central), streamer interaction quality (central), streamer credibility (central), monetary incentives (peripheral), bullet-screen consistency (peripheral), and popularity cues (peripheral).

2.3 Central route factors in LSC

Product information quality. According to Zhang et al., [14], product information quality is the usefulness, truthfulness, and vividness of the information related to a product that is conveyed in a live streaming session. In conventional e-business, product information quality is a key factor affecting consumers' trust and purchasing intention, and it has been continually identified [14]. The LSC can be used to show multi-sensory, real-time product demonstrations that can enhance the brightness and diagnostics of information, such as clothing try-ons, food tastings, or electronic device functions, unlike static text and images [15].

Streamer interaction quality. Streamer interaction quality is a measure of the interaction effectiveness and responsiveness between the streamer and viewers during a live session [16]. The streamer is a key component in LSC, communicating instead of static product descriptions but rather a conversational interaction [17]. Based on the literature of service interaction quality, three aspects of streamer interaction quality that are relevant to LSC were determined: real-time interaction (the timeliness and synchronicity of viewer and streamer interactions), responsiveness (the timeliness and relevance of the streamer's response to the viewer's questions), and empathy (the streamer's understanding of and reaction to individual viewer needs) [17].

Streamer credibility. Streamer credibility is defined by Song and Liu [18] as the degree to which a viewer considers a streamer to be an objective and trustworthy source of product information. Source credibility theory relates credibility to the acceptance and rejection of messages, in that credible sources are more influential since they are less likely to be rejected and more likely to be accepted. The three major elements of source credibility: trustworthiness, expertise and attractiveness. These dimensions are especially important in the LSC environment. Thus, when streamers are viewed as sincere and dependable, viewers become more trusting of broadcasters who advertise or advocate products [18].

2.4 Peripheral route factors in LSC

Bullet-screen consistency. Bullet-screen consistency is a consistency between the different bulletins that are simultaneously displayed on the live screen during streaming [19]. LSC's unique feature is bullet screens, short text comments posted by the viewers that scroll across the video display. Bullet screens are not static but rather dynamic, as they are synchronised in time with the live content, thus setting a context of co-viewing and social presence [19].

Monetary incentives. Monetary incentives include any monetary benefits or price reductions granted to the viewers during the live streaming session, such as low cost, coupons, prize draws, gifts and red packets [20]. Due to time or quantity limitations, monetary incentives are frequently scarce and urgent in LSC. Usually, these incentives are announced dynamically by the streamer, or they are simply displayed as a pop-up notification and must be acted upon by the viewer.

Popularity cues. The popularity cues of "many people list this live streaming room" or "this live streaming room has many fans" can be used as bandwagon signals to affect the attitudes and behaviours of consumers [9]. Social proof is a psychological concept in which a person's behaviour is based on the actions of others, which both dimensions suggest [20]. In LSC, popularity cues are very salient peripheral stimuli and are clearly visible on the interface [20].

2.5 Customer engagement

Customer engagement is a multidimensional psychological phenomenon consisting of affective, cognitive, behavioural and social elements that represent the individual's active experiences with a focal object or activity [7]. Engagement is not only about watching but also about participating, feeling and being socialised in the LSC context [15]. Affective engagement with the activity is the emotional involvement and sense of fun felt from the activity. Behavioural engagement refers to the visible aspects of engagement, including sharing of ideas, requests for information, product recommendations, following a streamer, and monitoring seller behaviour.

2.6 SII

Susceptibility to informational influence is a person's tendency to consider information conveyed by others as evidence of reality, especially when encountering product uncertainty or lack of prior experience [21]. SII is especially relevant in the LSC context, as there are many social information screens (SII) on the walls that display other people's opinions, many viewers counters that track popularity, and streamers (experts) that offer advice. Consumers with high SII will be more likely to use cues from the periphery (indicators of popularity via bullet screens and consensus from trusted streamers) to help guide their engagement and purchase decision-making. On the other hand, consumers with a low level of SII might use more of a central route to process the product information, consider the quality of the product information independently, and not be influenced by others' perceptions as easily [21].

2.7 Customer purchase intention

Customer purchase intention (CPI) is the extent to which a customer is likely or willing to make a purchase and is a subjective probability or intent to purchase a product or service [22]. In the context of e-commerce research, purchase intention is the most used dependent variable, as it is directly related to actual purchases and conversion rates. Purchase intention is influenced not only by cognition evaluations (such as product information quality perceived value) but also by affective state (such as enjoyment and engagement) [15–16]. Figure 1 presents the conceptual framework of this study delineates the relationships between variables involved in LSC using the ELM and SOR framework.

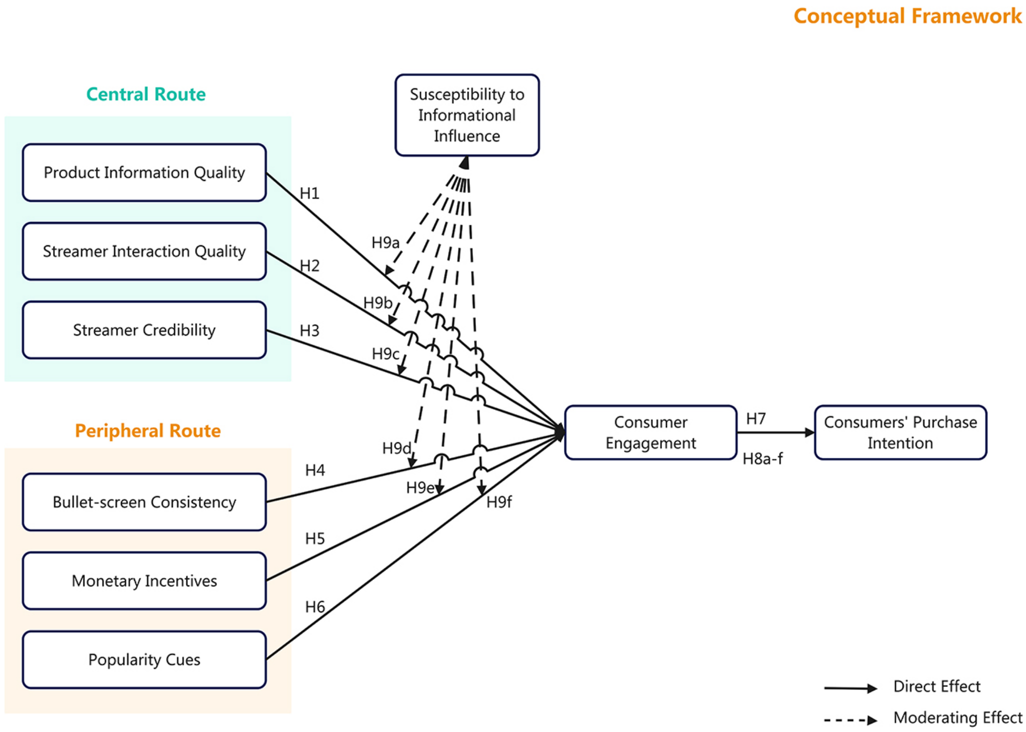

Fig. 1. Conceptual framework

3 METHODOLOGY

3.1 Research design

A quantitative research design was used in this study because it was more in line with the positivist tradition of the study. The deductive approach was used, which started with a theoretical model that was followed by the formulation of testable hypotheses and then the gathering of empirical data to verify or falsify the theoretical relationships.

3.2 Population and sampling

This study focused on Chinese Millennial live-stream shopping users, a digitally native generation that accounts for approximately 80% of live-stream shoppers in

China and represents a key consumer segment for understanding live-streaming commerce. The unit of analysis was the individual consumer. Using G*Power, the minimum required sample size was 113; however, a target of 500 respondents was adopted to improve statistical robustness. As no sampling frame was available, non-probability purposive sampling was employed, with participants required to be Chinese citizens, born in or after 1981, and to have used live-stream shopping platforms for at least two months.

3.3 Data collection procedure

Primary data were collected through an online survey developed using Wenjuanxing (https://www.wjx.cn/). The survey link was distributed via major Chinese social media channels, including WeChat and Weibo, from October to December 2024. All data collection procedures strictly adhered to ethical standards, including obtaining informed consent from all participants prior to their involvement and ensuring the confidentiality of their responses. Participants who failed to meet the eligibility criteria were excluded from further analysis.

3.4 Research instrument

The questionnaire consisted of four sections. Section A collected respondents' live-streaming e-commerce usage information, including preferred platforms, purchase frequency, duration of use, and product categories purchased. Sections B and C measured the study constructs using validated scales adapted to the live-streaming commerce context. Section D gathered demographic information, including gender, age, education, monthly income, and occupation. Nominal and ordinal scales were used for demographic and usage questions, while all construct items were measured using a five-point Likert scale. The questionnaire contained 68 measurement items representing nine constructs.

All measurement scales were adopted from previously validated studies to ensure content validity and reliability. Specifically, product information quality and streamer interaction quality were adapted from Zhang et al. [14]; streamer credibility from Ohanian [23]; bullet-screen consistency from Luo et al. [6]; customer engagement from Vivek et al. [24]; SII from Chen et al. [21]; and CPI from Chen et al. [21].

3.5 Data analysis

Data were analysed using SPSS 28 and SmartPLS 4.0.8.9. Data screening included missing values, outliers, normality, and common method variance. The measurement model was assessed for reliability and validity, while the structural model was evaluated using path coefficients, R^2, and VIF. Hypotheses, including mediation and moderation effects, were tested using bootstrapping (5,000 resamples), with statistical significance established at $p < 0.05$.

4 RESULTS AND DISCUSSION

A total of 500 valid responses were retained for analysis. No missing data were observed because all survey items were mandatory in the online questionnaire, preventing incomplete submissions. The dataset was further screened to remove careless responses, resulting in a complete and reliable dataset for subsequent analysis.

Table 1 shows the constructs were all measured with a five-point Likert scale, with moderate positive responses recorded in terms of the mean for the constructs studied, with the means ranging from 3.52 (SII) to 4.18 (Monetary Incentives). The mean score for Monetary Incentives (M = 4.18, SD = 0.74) was the highest of all the means, indicating that shoppers who live stream greatly appreciate monetary incentives like coupons and exclusive discounts. Another set of relatively high means (Popularity Cues, M = 4.05, SD = 0.79) underscored the significance of bandwagon cues in the LSC context. The means for CPI (M = 3.89, SD = 0.81) and Product Information Quality (M = 3.85, SD = 0.78) had favourable ratings, while the lowest means were found for Bullet-screen Consistency (M = 3.62, SD = 0.91) and SII (M = 3.52, SD = 0.94), which were still above the midpoint.

Table 1. Descriptive statistics

Construct	N	Minimum	Maximum	Mean	Std. Deviation
Product Information Quality	500	1	5	3.85	0.78
Streamer Interaction Quality	500	1	5	3.92	0.82
Streamer Credibility	500	1	5	3.78	0.85
Bullet-screen Consistency	500	1	5	3.62	0.91
Monetary Incentives	500	1	5	4.18	0.74
Popularity Cues	500	1	5	4.05	0.79
Customer Engagement	500	1	5	3.71	0.88
SII	500	1	5	3.52	0.94
CPI	500	1	5	3.89	0.81

Table 2 indicates that all constructs are positively correlated ($p < 0.01$), with the strongest correlation between Customer Engagement with CPI ($r = 0.58$), followed by the correlation between Product Information Quality and CPI ($r = 0.53$) and the correlation between Streamer Interaction Quality and CPI ($r = 0.50$). SII showed the lowest correlations, mostly with Monetary Incentives ($r = 0.19$) and Streamer Credibility ($r = 0.22$).

Table 2. Correlation matrix

Variable	1	2	3	4	5	6	7	8	9
1. Product Information Quality	1								
2. Streamer Interaction Quality	0.48**	1							
3. Streamer Credibility	0.42**	0.55**	1						
4. Bullet-screen Consistency	0.35**	0.38**	0.41**	1					
5. Monetary Incentives	0.31**	0.29**	0.33**	0.27**	1				
6. Popularity Cues	0.36**	0.41**	0.39**	0.32**	0.44**	1			
7. Customer Engagement	0.51**	0.54**	0.47**	0.39**	0.38**	0.42**	1		
8. SII	0.28**	0.25**	0.22**	0.31**	0.19**	0.26**	0.35**	1	
9. CPI	0.53**	0.50**	0.44**	0.36**	0.41**	0.45**	0.58**	0.30**	1

Note: **Correlation is significant at the 0.01.

4.1 Measurement model assessment

Table 3 shows the constructs exhibited adequate reliability (Cronbach's α values ranged from 0.824 to 0.912, which are all above the recommended level of 0.70; the composite reliability (CR) values ranged from 0.881 to 0.938, which are all above the recommended level of 0.70; and average variance extracted (AVE) values were between 0.621 and 0.776, meeting the 0.50 recommended level). The values of internal consistency, CR, and the AVE for Streamer Credibility were the highest (α = 0.912, CR = 0.938, AVE = 0.753) among the three, while those for SII were relatively low, but still acceptable (α = 0.824, CR = 0.881, AVE = 0.621). Figure 2 shows the established measurement model, which indicates all variables' dimensions along with their indicators and path relationships among study variables.

Table 3. Measurement model – reliability and convergent validity

Construct/Dimension	Cronbach's α	CR (ρc)	AVE
Product Information Quality	0.891	0.922	0.703
Usefulness			
Believability			
Vividness			
Streamer Interaction Quality	0.902	0.931	0.729
Real-time Interaction			
Responsiveness			
Empathy			
Streamer Credibility	0.912	0.938	0.753
Trustworthiness			
Expertise			
Attractiveness			
Bullet-screen Consistency	0.856	0.912	0.776
Monetary Incentives	0.888	0.919	0.695
Popularity Cues	0.879	0.915	0.684
Customer Engagement	0.903	0.933	0.699
Affective Engagement			
Cognitive Engagement			
Behavioural Engagement			
Social Engagement			
SII	0.824	0.881	0.621
CPI	0.867	0.909	0.714

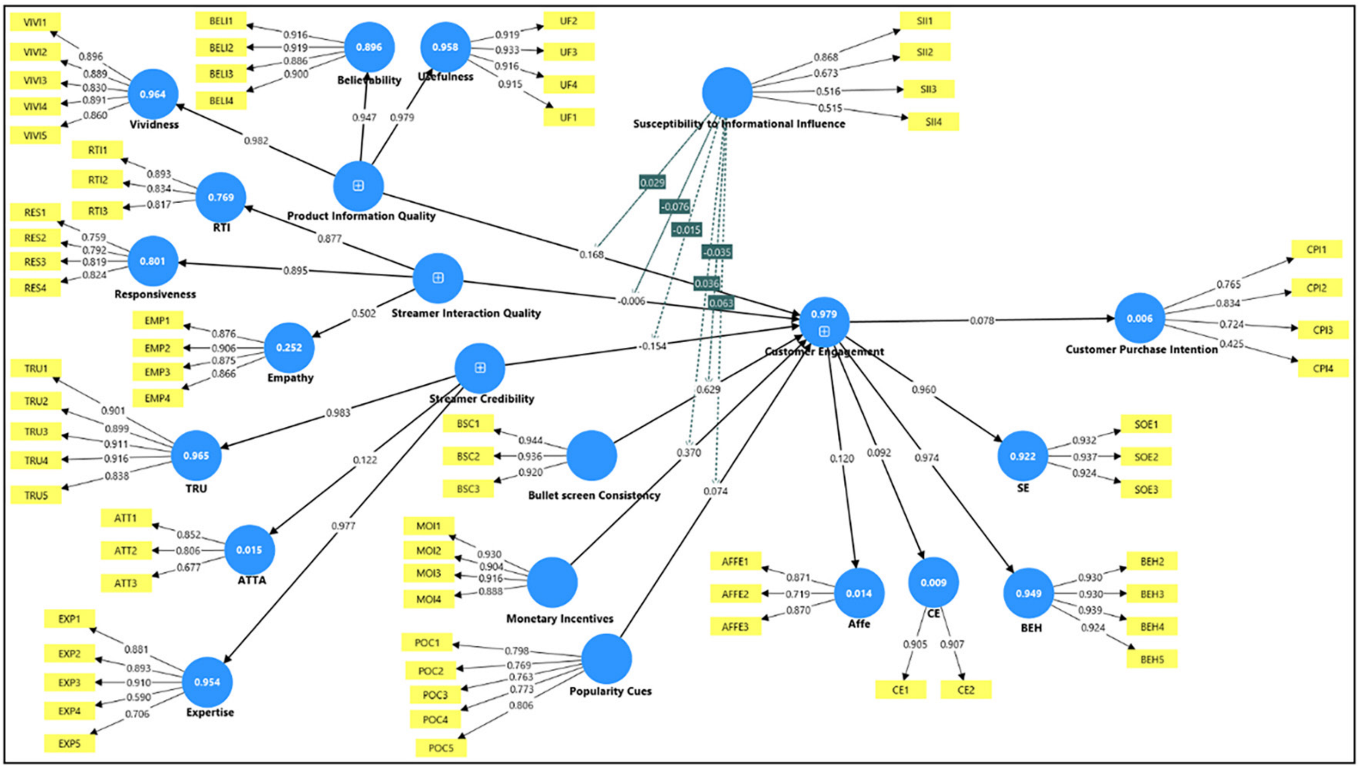

Fig. 2. Measurement model using PLS SEM

Table 4. Fornell-Larcker criterion – discriminant validity

Construct	1	2	3	4	5	6	7	8	9
1. Product Information Quality	0.838								
2. Streamer Interaction Quality	0.483	0.854							
3. Streamer Credibility	0.421	0.552	0.868						
4. Bullet-screen Consistency	0.352	0.379	0.408	0.881					
5. Monetary Incentives	0.312	0.286	0.335	0.274	0.834				
6. Popularity Cues	0.365	0.414	0.391	0.319	0.439	0.827			
7. Customer Engagement	0.508	0.541	0.472	0.387	0.381	0.422	0.836		
8. SII	0.281	0.251	0.224	0.311	0.192	0.263	0.354	0.788	
9. CPI	0.526	0.502	0.442	0.358	0.409	0.447	0.577	0.297	0.845

Table 4 confirms the square root of the AVE for each construct is higher than all inter-construct correlations (off-diagonal values), which confirms the discriminant validity. However, the maximum correlation is 0.577 between Customer Engagement and CPI, with the square root of the AVE for Customer Engagement (0.836) and CPI (0.845) being far greater.

Table 5 shows the results of the full collinearity test, which shows that all of the variance inflation factor values are <3.3, which is considered the conservative threshold. This suggests that common method bias is not a problem in this study since one variable alone does not explain most of the variance between constructs.

Table 5. Full collinearity test for common method bias

Construct	VIF
Product Information Quality	1.89
Streamer Interaction Quality	2.18
Streamer Credibility	1.76
Bullet-screen Consistency	1.58
Monetary Incentives	1.42
Popularity Cues	1.67
Customer Engagement	2.05
SII	1.51
CPI	1.95

4.2 Structural path assessment

The structural model assessed the direct, mediating, and moderating relationships using bootstrapping with 5,000 resamples. The model demonstrated moderate explanatory power, explaining 48.7% of the variance in customer engagement ($R^2 = 0.487$) and 52.3% of the variance in purchase intention ($R^2 = 0.523$). Both endogenous constructs showed predictive relevance ($Q^2 > 0$).

Table 6. Structural path assessment results

Hypothesis	Path/Effect	β	t-Value	p-Value	95% CI (LL–UL)	Decision
Direct Effects						
H1	PIQ → CE	0.241	5.67	<0.001	[0.158, 0.324]	Supported
H2	SIQ → CE	0.285	6.92	<0.001	[0.204, 0.366]	Supported
H3	SC → CE	0.156	3.83	<0.001	[0.078, 0.234]	Supported
H4	BSC → CE	0.089	2.21	0.027	[0.012, 0.166]	Supported
H5	MI → CE	0.112	2.85	0.004	[0.036, 0.188]	Supported
H6	PC → CE	0.172	4.15	<0.001	[0.092, 0.252]	Supported
H7	CE → CPI	0.492	12.34	<0.001	[0.417, 0.567]	Supported
Mediating Effects (Indirect Effects)						
H8a	PIQ → CE → CPI	0.119	5.23	<0.001	[0.074, 0.164]	Supported
H8b	SIQ → CE → CPI	0.14	6.31	<0.001	[0.097, 0.183]	Supported
H8c	SC → CE → CPI	0.077	3.67	<0.001	[0.039, 0.115]	Supported
H8d	BSC → CE → CPI	0.044	2.15	0.032	[0.005, 0.083]	Supported
H8e	MI → CE → CPI	0.055	2.79	0.005	[0.017, 0.093]	Supported
H8f	PC → CE → CPI	0.085	3.98	<0.001	[0.044, 0.126]	Supported

(Continued)

Table 6. Structural path assessment results *(Continued)*

Hypothesis	Path/Effect	β	t-Value	p-Value	95% CI (LL–UL)	Decision
Moderating Effects (Interaction Terms)						
H9a	PIQ × SII → CE	–0.058	1.92	0.055	[–0.117, 0.001]	Not supported
H9b	SIQ × SII → CE	–0.042	1.45	0.147	[–0.099, 0.015]	Not supported
H9c	SC × SII → CE	0.073	2.35	0.019	[0.014, 0.132]	Supported
H9d	BSC × SII → CE	0.112	3.64	<0.001	[0.053, 0.171]	Supported
H9e	MI × SII → CE	0.038	1.28	0.201	[–0.020, 0.096]	Not supported
H9f	PC × SII → CE	0.095	3.11	0.002	[0.037, 0.153]	Supported

Table 6 shows that all six persuasive information factors had significant positive effects on customer engagement (H1–H6, $p < 0.05$), with streamer interaction quality and product information quality exerting the strongest effects. Customer engagement also had a significant positive effect on purchase intention (H7, $p < 0.001$) and significantly mediated all relationships between persuasive information factors and purchase intention (H8a–H8f). SII significantly moderated the effects of streamer credibility, bullet-screen consistency, and popularity cues (H9c, H9d, H9f), but not product information quality, streamer interaction quality, or monetary incentives (H9a, H9b, H9e).

5 DISCUSSION

The findings demonstrate that all six persuasive information factors significantly enhanced customer engagement, supporting the view that both informational and social cues play important roles in live-streaming commerce. Among these factors, streamer interaction quality and product information quality exerted the strongest effects, indicating that consumers are more likely to engage when streamers provide responsive, interactive communication alongside useful and credible product information. This finding is consistent with prior studies showing that real-time interaction and high-quality information are fundamental drivers of consumer engagement in live-stream shopping environments.

Although streamer credibility, popularity cues, monetary incentives, and bullet-screen consistency also positively influenced engagement, their effects were comparatively weaker. This suggests that while social validation and promotional incentives remain relevant, Millennials place greater value on authentic interaction and informative content than on discounts or popularity signals alone. The relatively smaller effect of bullet-screen consistency may reflect the information overload commonly experienced during fast-paced live broadcasts, reducing consumers' reliance on peer comments. Furthermore, customer engagement had a strong positive effect on purchase intention, highlighting engagement as a key mechanism through which persuasive information shapes consumer behaviour.

The mediation analysis further revealed that customer engagement significantly mediated the relationships between all persuasive information factors and purchase intention. These findings support the SOR framework, suggesting that persuasive information (stimuli) influences purchase intention (response) primarily through customer engagement (organism). The strongest indirect effects were observed for streamer interaction quality and product information quality, emphasising that meaningful engagement is the primary pathway through which persuasive information translates into purchasing intentions.

Finally, SII significantly strengthened the effects of streamer credibility, bullet-screen consistency, and popularity cues, but did not moderate the effects of product information quality, streamer interaction quality, or monetary incentives. These results are consistent with the Heuristic-Systematic Model, indicating that consumers who rely more heavily on others' opinions are particularly responsive to social validation cues. In contrast, the influence of high-quality information and interactive communication appears robust regardless of individuals' susceptibility to external influence. Overall, the findings highlight the importance of combining informative content, interactive communication, and credible social signals to foster engagement and ultimately increase purchase intention in live-streaming commerce.

5.1 Practical implications

For live-streaming platforms, brands, and streamers, several actionable implications emerge. Firstly, consider interaction and information quality, which have the highest impacts on engagement and purchase intention – customers should be trained to be responsive, empathetic and genuine at the time of the stream. Second, the social validation cues (fans' numbers, consensus statements, etc.) do improve engagement amongst consumers who are more highly prone to information susceptibility, whereas the information and interaction quality cues work better for low-information-susceptible consumers. Third, "do not rely too much on monetary incentives, which have relatively less effects" (i.e., discounts should be used as additional measures, not as main drivers of engagement). Fourth, use the consistency of the bullets as a low-cost engagement booster, especially for users which are susceptible, and algorithmically highlight repetitive positive comments.

6 CONCLUSION AND RECOMMENDATION

This study extends the knowledge of purchase intention in live-streaming commerce by incorporating what we call persuasive information factors. This paper shows that customer engagement is a universal mediator of the path of social heuristic cues (streamer credibility, bullet-screen consistency, and popularity cues) on monetary incentives, whereas it is a selective mediator between systematic/utilitarian cues (information quality, interaction quality, and monetary incentives). Mediating role: the intervening role of customer engagement between social heuristic cues (streamer credibility, bullet-screen consistency, and popularity cues) and monetary incentives. Selective mediator: the intervening role of customer engagement between systematic/utilitarian cues (information quality, interaction quality, and monetary incentives). The results suggest a more detailed theory of live-streaming persuasion, and give practical suggestions for practitioners seeking to maximise engagement and conversion among Millennial consumers.

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