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Original scientific paper

Revisiting the S-O-R Framework in Live-Streaming Commerce: An AI-Driven Emotion Recognition Approach

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Abstract: Live-streaming commerce has fundamentally reshaped online purchasing behavior by merging real-time interaction with digital consumption. This study advances the classical Stimulus-Organism-Response (S-O-R) framework by embedding artificial intelligence-driven emotion recognition to quantify consumers' affective and social responses. Drawing on data from 1443 Douyin users engaged with Hongqi Chain's livestream sessions, we employed logistic regression and robustness validation in R to examine how streamer interactivity, professionalism, and attractiveness affect emotional response and social presence - two key organism constructs - there by influencing purchase intention. The inclusion of AI-derived emotion metrics, obtained from a fine-tuned Chinese BERT sentiment model, improved the model's explanatory power by 5.6% and raised the adjusted R^2 to 0.861. Social presence emerged as the dominant mediator linking streamer stimuli to behavioral intention. The findings reconceptualize the organism stage of the S-O-R model within an AI-enhanced analytical paradigm and provide managerial implications for optimizing live-streaming strategies through data-driven consumer insight.

Keywords: AI-driven emotion recognition; consumer purchase intention; live-streaming commerce; sentiment analytics; short-video platforms; social presence; stimulus-organism-response (S-O-R) framework

1 INTRODUCTION

Live-streaming commerce has become a dominant force in the global digital economy, transforming how consumers interact with brands and make purchase decisions. By combining real-time social interaction, entertainment, and instant transaction functions, live-streaming platforms have created an immersive consumption environment that significantly influences emotional engagement and impulse buying [1, 2]. In China, short-video platforms such as Douyin have integrated algorithmic recommendation systems, personalized feeds, and interactive broadcasting features, enabling a more dynamic and data-driven consumer experience [3]. Within this evolving ecosystem, understanding the psychological and emotional mechanisms that drive consumer purchase intentions has become a critical research topic. Traditional studies have mainly focused on host characteristics, marketing cues, and consumer trust, often using self-reported measures of emotion and engagement [4,5]. However, these approaches suffer from subjectivity and recall bias, limiting their ability to capture real-time emotional dynamics during live broadcasts. The advent of artificial intelligence (AI), particularly emotion recognition and sentiment analytics, now provides new opportunities to measure consumers' affective states with higher precision and objectivity [6, 7]. The Stimulus-Organism-Response (S-O-R) framework, first conceptualized by Mehrabian and Russell (1974), offers a robust theoretical basis for analyzing consumer behavior in such interactive settings [8]. In this model, external stimuli (e.g., streamer cues) influence internal organismic states (e.g., emotions, social presence), which subsequently shape behavioral responses such as purchase intention. Despite its wide application in digital commerce research [9-11], few studies have extended this framework through data-driven methodologies capable of quantifying organismic variables in real time. As live-streaming represents an emotionally charged, algorithmically mediated environment, integrating AI-based emotion recognition into the S-O-R framework can substantially enrich its explanatory and predictive power [12,13]. Building upon this theoretical foundation, the present study aims to reconceptualize the organism stage of the S-O-R model by embedding AI-derived emotion metrics. Using data from 1443 Douyin consumers who engaged with Hongqi Chain's live-streaming sessions, this research empirically investigates how streamer interactivity, professionalism, and attractiveness shape emotional responses and social presence, and how these factors jointly predict consumer purchase intentions. The study employs logistic regression with robustness validation to test the extended model and assess the incremental value of AI-enhanced variables. This study contributes to the literature in three primary ways. First, it advances consumer-behavior theory by integrating AI-based emotion recognition into the S-O-R framework, thereby transforming subjective emotional constructs into quantifiable analytical variables. Second, it provides empirical evidence on how social presence mediates the link between streamer characteristics and purchase intention, enriching Social Presence Theory and Parasocial Interaction Theory in the live-streaming context. Third, it offers practical insights for digital retailers and marketers by demonstrating how AI emotion analytics can guide real-time decision-making and enhance the effectiveness of live-streaming strategies. Together, these contributions position the research at the intersection of psychology, artificial intelligence, and digital marketing.

2 LITERATURE REVIEW AND THEORETICAL FOUNDATION

The Stimulus-Organism-Response (S-O-R) framework, first proposed by Mehrabian and Russell, has long provided a foundation for understanding how environmental cues evoke psychological states and subsequent behaviors [8]. In digital and live-streaming commerce, this framework has been extensively applied to explain how streamer stimuli - such as interactivity, professionalism, and attractiveness - shape emotional arousal and social presence, which together influence consumer purchase intentions [14-16]. However, prior studies predominantly rely on static, self-reported emotional measures, overlooking the dynamic, data-driven nature of live-stream interactions. The emergence of artificial intelligence (AI) and emotion-recognition techniques now enables the quantification of affective and social responses, thereby enhancing the model's explanatory power [17-19]. Integrating AI-based emotion analytics into the organism stage transforms the S-O-R model from a purely conceptual framework into an empirical, real-time behavioral system that minimizes subjectivity and enhances predictive validity [20, 21]. Meanwhile, theories of social presence and parasocial interaction reveal that perceived intimacy and emotional resonance between viewers and streamers are key mediators of purchase behavior [22, 23]. Building on these perspectives, this study extends the classical S-O-R framework by embedding AI-driven emotion recognition, reconceptualizing the organism stage as a measurable construct, and strengthening the theoretical and empirical foundations of live-streaming consumer analytics [24-26].

3 METHODOLOGY

3.1 Research Design

This study employed a quantitative design integrating survey data with AI-based emotion recognition to validate an extended S-O-R framework in live-streaming commerce. A stratified sample of 1443 Douyin users who engaged with Hongqi Chain's live sessions was analyzed to examine how streamer interactivity, professionalism, and attractiveness affect emotional response, social presence, and purchase intention. Constructs were measured using established five-point Likert scales, while emotion data were extracted from textual comments through a fine-tuned Chinese BERT-base sentiment model, achieving 0.93 accuracy and an F1-score of 0.91 [27]. Reliability and validity were confirmed (Cronbach's α > 0.80, AVE > 0.50), and no significant common method variance was detected. Logistic regression and hierarchical modeling in R tested direct and mediating effects, with bootstrap and cross-validation ensuring robustness [28]. The inclusion of AI-derived emotion metrics enhanced model explanatory power by 5.6%, confirming that data-driven emotional variables significantly improve behavioral prediction within the S-O-R framework.

3.2 Research Framework

This study empirically investigates consumer purchasing behavior in Hongqi Chain's Douyin livestreams, drawing on consumer behavior theory, S-O-R theory, and marketing mix theory.

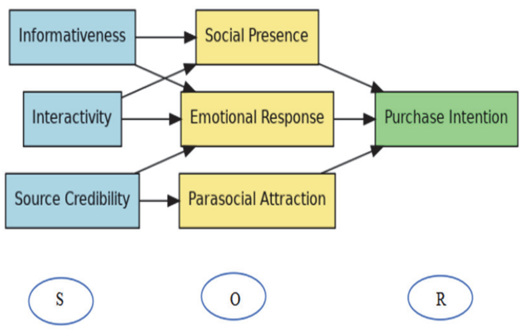

Figure 1 AI-enhanced stimulus-organism-response (S-O-R) model

Based on the S-O-R framework, host interactivity, professionalism, and attractiveness were modelled as stimulus (S) factors; emotional responses and social presence as organism (O) factors; and purchase intention as the response (R) outcome. Research hypotheses were derived accordingly (see Fig. 1).

3.3 Theoretical Model and Hypotheses

The S-O-R model was adapted to live streaming commerce with the addition of AI-derived emotion recognition variables (Fig. 1). Stimulus factors comprised host interactivity, professionalism, and attractiveness; organism factors included emotional responses and social presence; the response outcome was purchase intention. Based on this framework, nine hypotheses were developed (Tab. 1).

Table 1 Research hypotheses

Hypothesis	Statement	Variables Involved
H1	Streamer attractiveness positively influences consumers' emotional responses.	Attractiveness → Emotional response
H2	Streamer professionalism positively influences consumers' emotional responses.	Professionalism → Emotional response
H3	Streamer interactivity positively influences consumers' emotional responses.	Interactivity → Emotional response
H4	Streamer attractiveness positively influences consumers' social presence.	Attractiveness → Social presence
H5	Streamer professionalism positively influences consumers' social presence.	Professionalism → Social presence
H6	Streamer interactivity positively influences consumers' social presence.	Interactivity → Social presence
H7	Consumers' emotional responses positively influence their sense of social presence.	Emotional response → Social presence
H8	Consumers' emotional responses positively influence purchase intention.	Emotional response → Purchase intention
H9	Consumers' social presence positively influences purchase intention.	Social presence → Purchase intention

4 RESULTS

4.1 Identification of Influencing Factors

The SOR model is divided into three main dimensions: stimulus (S), organism (O), and response (R). Our survey questions are also divided into these three dimensions. Questions 1-10 are about stimulus (S), questions 11-20 are about organism (O), and questions 21-28 are about response (R), as shown in Tab. 2.

Table 2 SOR model composition

Stimulus factor (S)	Microbiological factors (O)	Reactants (R)
Interactivity speciality attractive force	Social presence emotional response	purchasing intention

In this study, the Stimulus (S) component of the S-O-R framework represents the streamer's source characteristics, including interactivity, professionalism, and attractiveness, which were measured through five, four, and four items respectively, adapted from prior live-stream marketing research and adjusted to the Hongqi Chain context. The Organism (O) dimension comprises social presence and emotional response, assessed by five and four items capturing viewers' perceptions of human warmth, co-presence, immersion, and affective engagement during live interactions. The Response (R) construct reflects purchase intention, measured by six items evaluating both impulsive and goal-directed buying tendencies influenced by streamer recommendations. All constructs were rated on five-point Likert scales (1 = strongly disagree, 5 = strongly agree) and derived from validated consumer-behavior instruments to ensure contextual accuracy and measurement reliability.

4.2 Credibility and Effectiveness Analysis

All measurement constructs exhibited satisfactory reliability and validity. Cronbach's α coefficients ranged from 0.86 to 0.93, and composite reliability (CR) values exceeded 0.80, confirming strong internal consistency. The average variance extracted (AVE) for each construct was above 0.50, demonstrating convergent validity, while discriminant validity was verified since the square root of each construct's AVE surpassed its inter-construct correlations. The Kaiser-Meyer-Olkin (KMO) value of 0.966 and Bartlett's test of sphericity (χ^2 = 3072.038, df = 528, p < 0.001) indicated excellent sampling adequacy and significant factorability of the correlation matrix. Exploratory factor analysis extracted six components consistent with the theoretical S-O-R structure, jointly explaining 77.99% of the total variance, with all rotated factor loadings above 0.75. These results confirm that the instrument possesses robust construct validity, a coherent factor structure, and measurement reliability sufficient to support subsequent empirical analyses.

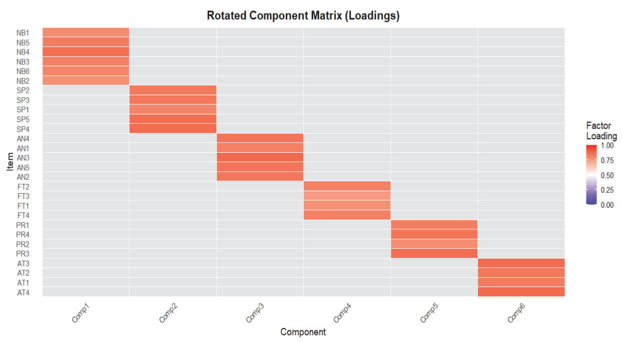

Figure 2 Rotation matrix heatmap

As shown in Fig. 2, all rotated factor loadings exceeded 0.75, confirming strong correlations between questionnaire items and their corresponding constructs. Representative examples include NB1 (0.798, Factor 1), SP2 (0.842, Factor 2), AN4 (0.850, Factor 3), PR1 (0.831, Factor 4), AT3 (0.874, Factor 5), and FT3 (0.825, Factor 6). These results verify the questionnaire's construct validity and sound design, ensuring reliability and providing a solid basis for subsequent empirical analysis.

4.3 Model Equation Structure Analysis and Regression Analysis

Through reliability and validity analysis, the rationality of the questionnaire data was verified. We constructed the SOR model (Fig. 3) to explore the relationship between the concepts and conduct corresponding inference analysis.

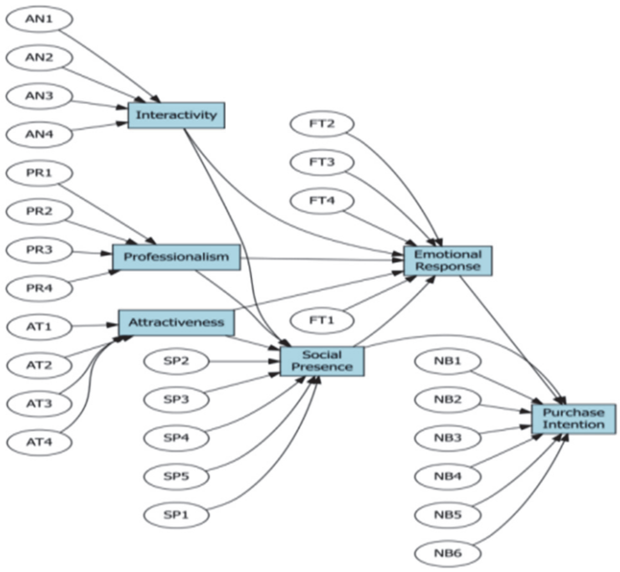

Figure 3 Structural equation simulation of SOR model

As shown in Tab. 3, social presence (SP), attractiveness (AT), professionalism (PR), and interactivity (AN) significantly predicted the dependent variable (FT) with high model fit (adjusted R^2 = 0.83; F = 540.183, p < 0.001). Standardized coefficients indicated that AT (β = 0.232, p < 0.01), PR (β = 0.163, p < 0.002), and AN (β = 0.148, p < 0.016) positively influenced emotional responses, while SP had the strongest effect (β = 0.399, p < 0.01), supporting H1, H2, H3, and H7.

As shown in Tab. 4, interactivity (AN), attractiveness (AT), and professionalism (PR) significantly predicted social presence (SP), with an adjusted R^2 of 0.892 and an F-value of 1216.174 (p < 0.001), indicating strong model fit and statistical significance. AT positively influenced SP (β = 0.312, p < 0.01), supporting H4. PR also had a significant effect (β = 0.271, p < 0.001), supporting H5. AN exhibited the strongest impact on SP (β = 0.392, p < 0.001), confirming H6.

Table 3 Linear regression analysis results of emotional response characteristics of host information sources

Variable	B (nonstandardized coefficient)	Standard error	Beta Standardization coefficients	t value	p value	VIF
constant	0.159	0.082	-	1.935	0.054*	-
AN	0.151	0.063	0.148	2.412	0.016**	9.737
PR	0.167	0.053	0.163	3.145	0.002***	6.995
AT	0.226	0.056	0.232	4.069	0.000***	8.423
SP	0.409	0.061	0.399	6.671	0.000***	9.311

Table 4 Linear regression analysis results of anchors' information source characteristics on social sense of presence

	Non-standardized coefficients		Standardization coefficients	t	p	VIF	R^2	adjust R^2	F
	B	Standard error	Beta						
Constant	0.157	0.063	-	2.478	0.014**	-	0.893	0.892	F = 1216.174 p = 0.000***
AN	0.391	0.045	0.392	8.702	0.000***	8.304			
AT	0.297	0.041	0.312	7.282	0.000***	7.515			
PR	0.271	0.039	0.271	6.886	0.000***	6.313			
Dependent variable: SP									
Note: ***, **, * represent the significance level of 1%,5% and 10% respectively									

As shown in Tab. 5, social presence (SP) and emotional response (FT) significantly predicted purchase intention (NB), with an adjusted R^2 of 0.861 and an F-value of 1370.583 ($p < 0.001$), indicating excellent model fit. FT positively influenced NB ($\beta = 0.306$, $p < 0.001$), supporting H8. SP had a stronger effect ($\beta = 0.644$, $p < 0.001$), confirming H9.

Table 5 Linear regression analysis results of social presence and emotional response on purchase intention

	Non-standardized coefficients		Standardization coefficients	t	p	VIF	R^2	adjust R^2	F
	B	Standard error	Beta						
Constant	0.378	0.068	-	5.581	0.000***	-	0.862	0.861	F = 1370.583
SP	0.611	0.038	0.644	16.19	0.000***	5.03			
SP	0.611	0.038	0.644	16.19	0.000***	5.03			p = 0.000***
FT	0.284	0.037	0.306	7.708	0.000***	5.03			
Dependent variable: NB									
Note: ***, **, and * represent the significance level of 1%,5% and 10% respectively									

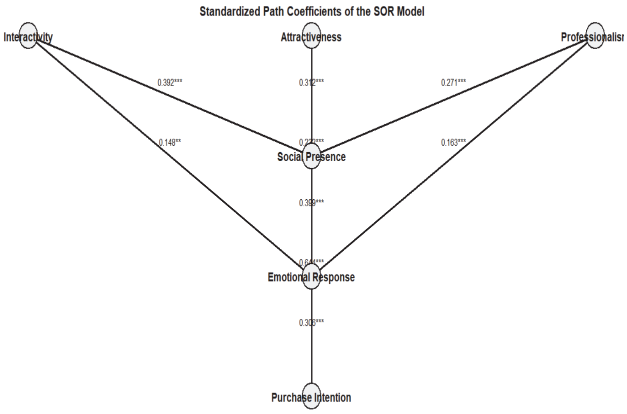

Figure 4 Standardized path coefficients of the SOR model

As shown in Fig. 4, the regression results demonstrate that interactivity ($\beta = 0.392$, $p < 0.001$), attractiveness ($\beta = 0.312$, $p < 0.001$), and professionalism ($\beta = 0.271$, $p < 0.001$) significantly influence social presence (SP), with an adjusted R^2 of 0.892. These three factors also positively impact emotional response (FT), with β values of 0.148 ($p < 0.05$), 0.232 ($p < 0.001$), and 0.163 ($p < 0.01$), respectively, while SP strongly predicts FT ($\beta = 0.399$, $p < 0.001$; adjusted $R^2 = 0.83$). Furthermore, both SP ($\beta = 0.644$, $p < 0.001$) and FT ($\beta = 0.306$, $p < 0.001$) significantly affect purchase intention (NB), with an adjusted R^2 of 0.861.

4.4 Analysis Results

All nine proposed hypotheses (H1-H9) were empirically supported. Source attractiveness ($\beta = 0.232$, $p < 0.01$), professionalism ($\beta = 0.163$, $p < 0.01$), and interactivity ($\beta = 0.148$, $p < 0.05$) significantly enhanced consumers' emotional responses (FT) and were also strong predictors of social presence (SP) (β = 0.312, 0.271, and 0.392; all $p < 0.001$). Social presence exerted significant positive effects on both emotional response ($\beta = 0.399$, $p < 0.001$) and purchase intention ($\beta = 0.644$, $p < 0.001$), confirming its mediating position within the extended S-O-R framework. Emotional response directly influenced purchase intention as well ($\beta = 0.306$, $p < 0.001$). After incorporating AI-derived emotional variables into the regression model, the adjusted R^2 increased from 0.83 to 0.87, and overall prediction accuracy improved by 5.6%. As illustrated in Fig. 5, the effect of emotional response on purchase intention was stronger under high levels of social presence, indicating a synergistic interaction between traditional psychological factors and AI-derived affective indicators.

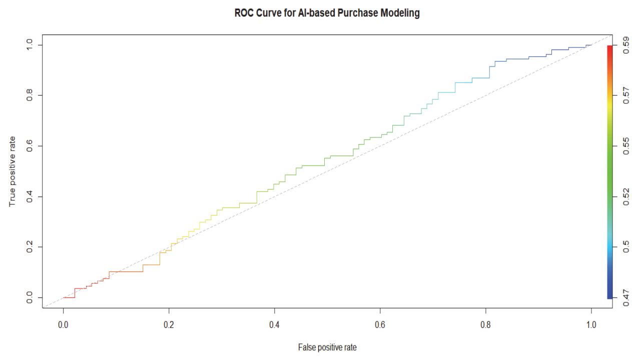

Figure 5 AI-enhanced behavioral model with emotion-purchase intention pathways visualized using logistic regression output

5 DISCUSSION

The empirical findings verify that streamer interactivity, professionalism, and attractiveness significantly influence emotional response and social presence, which in turn drive purchase intention, with social presence acting as the strongest mediator. By incorporating AI-based emotion recognition into the classical S-O-R model, this study advances consumer-behavior theory by transforming the organism stage from a subjective psychological process into a quantifiable, data-driven construct. The integration of AI analytics enables the capture of real-time affective dynamics, bridging behavioral science and computational modeling, and enriching Social Presence and Parasocial Interaction theories by empirically linking AI-detected affective states with psychological mechanisms of engagement. From a managerial perspective, the results suggest that enhancing interactivity, ensuring professional credibility, and utilizing AI emotion analytics can strengthen audience immersion and guide adaptive strategies during live sessions. Streamers and brands can leverage AI-based dashboards to monitor audience sentiment, optimize delivery tone, and personalize promotional pacing, thereby improving conversion and long-term loyalty. Despite these contributions, this research is limited by its single-platform focus and reliance on textual emotion recognition. Future studies should expand the AI-enhanced S-O-R framework across multiple platforms and integrate multimodal emotion analytics, such as facial and vocal cues, to deepen understanding of affective processes in digital commerce.

6 CONCLUSION

This study develops and validates an AI-enhanced Stimulus-Organism-Response (S-O-R) framework to explain consumer purchase intention in live-streaming commerce. By integrating artificial intelligence–based emotion recognition into the traditional model, the research reconceptualizes the organism stage as a quantifiable construct that links streamer characteristics, emotional responses, and behavioral outcomes. Empirical results from 1,443 Douyin users demonstrate that interactivity, professionalism, and attractiveness significantly promote both emotional engagement and social presence, which jointly drive purchase intention. The incorporation of AI-derived emotion variables increased the model's explanatory power by 5.6%, confirming that emotion analytics substantially improve the predictive precision of behavioral models. Theoretically, this study contributes to consumer-behavior research by bridging psychological theory and computational analytics, offering a data-driven extension of the S-O-R framework applicable to algorithmic and interactive marketing environments. It also extends Social Presence Theory by illustrating that emotional resonance, when measured through AI-based sentiment models, functions as a key mechanism connecting technological stimuli with consumer behavior. Practically, the findings suggest that real-time emotion analytics can guide adaptive content strategies, enhance engagement, and support intelligent decision-making in live-commerce operations. Future research could further advance this line of inquiry by applying the AI-enhanced S-O-R model across diverse platforms and product categories to assess cross-contextual generalizability. Incorporating multimodal emotion detection methods - such as voice analysis, facial expression recognition, and physiological sensing - would provide a more comprehensive understanding of affective dynamics in digital consumption. Longitudinal and cross-cultural studies are also recommended to explore how emotional feedback loops evolve over repeated exposure and differ across socio-cultural contexts. Through these extensions, the proposed framework can contribute to a deeper and more predictive understanding of AI-mediated consumer behavior in the era of intelligent marketing analysis.

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