Journal of Management Science Research Review
https://jmsrr.com/index.php/Journal/about

Volume 5 Issue No 2 (2026)

Online ISSN: 3006-2047
Print ISSN: 3006-2039

From Screens to Shopping Carts: How Information Quality and Interaction Quality in Live-Streaming Commerce Drive Compulsive Buying Behavior

Huzaifa Ali
Air University School of Management, Air University Islamabad, Multan Campus
Chhuzaifaali6477@gmail.com

Nayab Aslam
Air University School of Management, Air University Islamabad, Multan Campus
Malikaslam66850@gamil.com

Moin Ahmad Moon*
Air University School of Management, Air University, Islamabad, Multan Campus
Email: Moin@aumc.edu.pk

Memoona Imran
Air University School of Management, Air University Islamabad, Multan Campus
Moonaimran1718@gmail.com

Abstract

The rapid proliferation of live-streaming commerce has reshaped consumer–seller relationships, blurring the boundary between entertainment and shopping. While streamers cultivate intimacy with viewers, this same intimacy may exacerbate maladaptive consumption patterns, most notably compulsive buying behavior (CBB). Drawing on Social Presence Theory, Para-Social Interaction Theory, and Social Comparison Theory, this study tests a model in which information quality and interaction quality act as twin streamer-controlled stimuli influencing three parallel psychosocial mediators parasocial interaction (PSI), social presence, and upward social comparison which in turn drive CBB, with self-discrepancy positioned as a moderator. A quantitative cross-sectional design was employed, drawing on survey data from 229 young consumers aged 18 to 35 years in Pakistan who actively engage with live-streaming commerce. Data were analyzed using covariance-based structural equation modeling (CB-SEM) in IBM SPSS Statistics (v.27) and IBM SPSS AMOS (v.24), following the two-step procedure of Anderson and Gerbing (1988). The structural model showed that information quality and interaction quality significantly predicted PSI, social presence, and upward social comparison, and that PSI ($\beta = .815$), upward social comparison ($\beta = .387$), and self-discrepancy were significant positive predictors of CBB, whereas social presence exerted a small negative effect ($\beta = -.211$). The model explained 83% of the variance in CBB. The study advances theory by integrating media-effects and consumer-psychology streams and offers implications for platform designers, marketers, and policymakers.

Keywords: Parasocial Interaction; Social Presence; Upward Social Comparison; Compulsive Buying Behavior; Information Quality; Interaction Quality; Self-Discrepancy

Introduction

As of writing this, live-streaming commerce has surged to become a critical retail channel across the globe, as platforms like TikTok Live, Instagram Live, YouTube Live, and Daraz Live merge real-time content streaming, social interaction and instant purchasing in one immersive sense of the word. Live commerce had over 526 million users in China alone, and similar trends are reported in South Asia, Southeast Asia, and the United States (Jiang et al., 2024). It is a way of creating a "streamer marketing funnel" in one shot, giving streamers a chance to answer questions as they go live, and making checkout buttons pop up on the stream as it is raging live. While the monetary benefits accrue for the sellers, there are growing concerns regarding the psychological impact on viewers who often experience regret between repeated and excessive purchases after long viewing sessions (Sharma et al., 2026). Compulsive shopping, an ongoing and recurrent shopping pattern that occurs as a predominant response to negative emotions or unmet needs (Faber & O'Guinn, 1992; Ridgway et al., 2008), has become a well-documented phenomenon of immersive online shopping. CBB has been linked to social media usage, high materialism, low self-control, and social comparison, as suggested in recent reviews (Biling et al., 2023; Moon & Attiq, 2018a; Sharma et al., 2026). Evidence from emerging economies further documents the prevalence and behavioral antecedents of compulsive buying among young consumers (Moon & Attiq, 2018b; Moon, Faheem, & Farooq, 2022), and recent work links immersive, interactive digital environments directly to compulsive consumption (Moon, 2026).

While research has explored factors that precede and follow media use, few studies have examined the kinds of stimuli that occur first such as the quality of information presented by a streamer and the quality of interactions during the broadcast as upstream catalysts influencing compulsive consumption. Jiang et al. (2024) highlighted the interconnections among information quality, interaction quality, social presence, and consumers' purchase intention in social media live streaming, but lacked compulsive outcomes and a parallel multi-mediator model. Communication research has revealed that PSI is at the heart of creating the illusion of feedback between the audience and media subjects (Horton & Wohl, 1956). Chinchilla and Kim (2025) reported that streamers' self-disclosure cues boosted social presence, in turn increasing PSI and viewer enjoyment. This presents a fruitful direction: if streamer-administered streams induce PSI, then these same streams could also trigger maladaptive states such as upward social comparison and, eventually, CBB.

While some stream-level quality cues have been linked to compulsive buying behavior, no previous integrated research has combined three parallel mediators (PSI,

Volume 5 Issue No 2 (2026)

Online ISSN: 3006-2047
Print ISSN: 3006-2039

social presence, and upward social comparison) to explain the link between stream-level quality cues and compulsive buying behavior, while modeling individual vulnerability through the self-discrepancy concept. This study fills that gap. The psychosocial states are conceptualized as parallel organisms within the stimulus–organism–response (S-O-R) model (Mehrabian & Russell, 1974); information quality and interaction quality are treated as twin stimuli, and self-discrepancy moderates the conversion of psychosocial states into compulsive purchasing (Higgins, 1987). The study pursues four objectives: (a) to test the direct effects of the quality cues on the mediators, (b) to test the direct effects of each mediator on CBB, (c) to examine the indirect mediated pathways between the quality cues and CBB, and (d) to test the moderating effect of self-discrepancy. The remainder of the article presents the theoretical background and study hypotheses, followed by methods, results, implications, and limitations.

Theoretical background

The proposed model is based on three complementary theories. The first is Social Presence Theory (Short et al., 1976), which holds that media vary in their capacity to highlight the presence of another and that greater salience of the other increases emotional engagement and behavioral compliance. In this context, information quality and interaction quality strengthen the viewer's perception of the streamer as a "real" social other, increasing the sense of being bonded to the streamer. Second, Para-Social Interaction Theory (Horton & Wohl, 1956) suggests that audiences form one-sided relationships with media figures, experiencing a sense of intimacy and reciprocity. This sense of personal connection reduces critical evaluation of marketed products and leads to increased compulsive purchasing. Third, Social Comparison Theory (Festinger, 1954), extended through Self-Discrepancy Theory (Higgins, 1987), accounts for how rich and interactive streams elevate upward social comparison, whereby viewers with greater actual–ideal discrepancies are more likely to engage in compulsive purchasing when psychosocial discrepancy is high.

Extension through the S-O-R framework

These theories converge within the S-O-R framework (Mehrabian & Russell, 1974): stream-level qualities (S) influence psychosocial organisms (O)—PSI, social presence, and upward social comparison—which produce a behavioral response (R) in the form of CBB, with self-discrepancy serving as an individual-level boundary condition. By embedding three media-effects and consumer-psychology constructs within a single stimulus–organism–response architecture, the model extends prior live-commerce frameworks that have terminated at purchase intention and treats compulsive consumption as the ultimate behavioral response of interest. Figure 1 displays the theoretical model for this study.

Volume 5 Issue No 2 (2026)
Online ISSN: 3006-2047
Print ISSN: 3006-2039

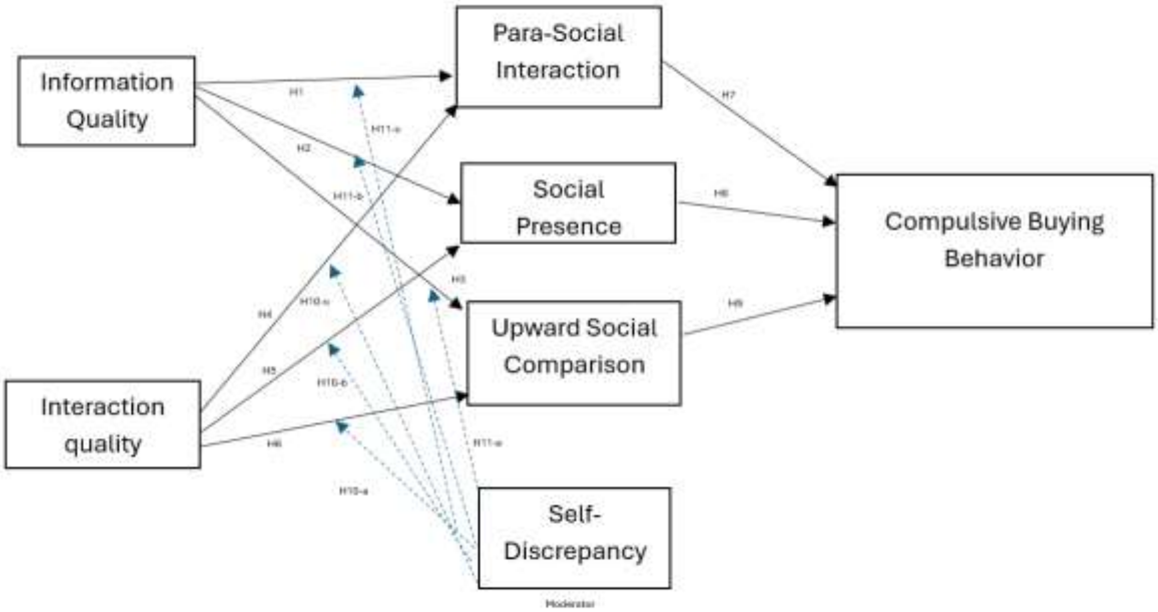

Figure 1
Theoretical Model
Note. Information quality and interaction quality act as twin stimuli influencing three parallel mediators (PSI, social presence, and upward social comparison), which drive compulsive buying behavior. Self-discrepancy moderates the mediator-to-outcome paths.

Literature review and hypothesis development

Information quality

Information quality is the degree to which information provided by a streamer is believed to be true, useful, vivid, accurate, and relevant to the user's decision-making task (DeLone & McLean, 2003; Jiang et al., 2024). For this study, it is defined along three dimensions: believability, usefulness, and vividness. High-quality product information can reduce uncertainty and build trust through real-time visual narration in the live stream (Sun et al., 2019). While the influence of information quality on perceived social presence and purchase intention has been theorized and empirically confirmed, the relationship between information quality and perceived social presence in turn influencing CBB has not been sufficiently studied (Jiang et al., 2024; Wongkitrungrueng & Assarut, 2020). Accordingly, we hypothesize:
H1. Information quality positively influences parasocial interaction.
H2. Information quality positively influences social presence.
H3. Information quality has a positive influence on upward social comparison.

Interaction quality

Interaction quality refers to how responsive, real-time, empathetic, and customized a streamer appears toward viewers (Jiang et al., 2024). It is defined in this study as

Online ISSN: 3006-2047
Print ISSN: 3006-2039

responsiveness, interaction-as-it-happens, and empathy. Based on interactivity scales developed for digital media (Liu & Shrum, 2002), it distinguishes live streaming from pre-recorded media by making recipients active. High interaction quality has been found to increase social presence (Jiang et al., 2024), enhance parasocial bonds (Chinchilla & Kim, 2025; Hu et al., 2017), and reinforce actions such as gifting or repeat viewing (Lu & Chen, 2021). The negative effects of this behavior, especially how it may seed CBB through parasocial and social-comparison processes, are understudied. We therefore hypothesize:

H4. Interaction quality positively influences parasocial interaction.

H5. Interaction quality positively influences social presence.

H6. Interaction quality has a positive influence on upward social comparison.

Parasocial interaction

The extent to which an audience purportedly knows, interacts with, and cares about a media persona is described as parasocial interaction (PSI), first introduced by Horton and Wohl (1956). PSI is heightened in live streaming due to perceptions of immediacy, self-disclosure, and conversational communication style (Chinchilla & Kim, 2025). Prior research shows that individuals develop brand attachment, brand loyalty, and greater purchase intent toward PSI targets (Hu et al., 2017; Sokolova & Kefi, 2020); moreover, PSI can foster uncritical consumption when followers seek to emulate attractive individuals (Lee & Watkins, 2016). Accordingly, we postulate:

H7. Parasocial interaction positively influences compulsive buying behavior.

Social presence

Short et al. (1976) define social presence as the level of “realness” feeling warm, close, involved, and real in the presence of another during communication. Live streaming creates high social presence because it combines synchronous audio-visual information with interactivity through chat channels (Chinchilla & Kim, 2025). Empirical results from Jiang et al. (2024) and Wongkitrungrueng and Assarut (2020) show that social presence positively affects trust, perceived enjoyment, and purchase intention; however, its role in increasing compulsive purchasing by lowering psychological barriers has yet to be explored. We therefore hypothesize:

H8. Social presence positively influences compulsive buying behavior.

Upward social comparison

Upward social comparison occurs when individuals compare themselves with others perceived to be superior on a salient dimension (Festinger, 1954). On live-streaming platforms, viewers are repeatedly exposed to streamers who curate enviable lifestyles and appearances, fueling comparisons that erode well-being and seed materialistic aspirations (Ling et al., 2023). Research has linked upward social comparison to envy, materialism, and online compulsive buying (Ling et al., 2023; Liu et al., 2019), yet the role of stream-level cues as antecedents of such comparison within live commerce is not well documented. Accordingly, we hypothesize:

H9. Upward social comparison positively influences compulsive buying behavior.

Compulsive buying behavior

Compulsive buying behavior is conceptualized as a chronic, repetitive, and uncontrollable purchasing pattern functioning as a response to negative affect or unmet psychological needs (Faber & O'Guinn, 1992; Ridgway et al., 2008). Reviews and empirical studies consistently identify materialism, low self-control, anxiety, social-media intensity, self-conceptual traits, and parasocial bonds as antecedents of CBB (Ling et al., 2023; Moon, Faheem, & Farooq, 2022; Moon, Rasool, & Attiq, 2015a; Sharma et al., 2026). Social-shopping motives in particular have been shown to differentiate impulsive from compulsive buying patterns (Moon, Farooq, & Kiran, 2017), while individual-difference and personality factors shape susceptibility to irregular buying (Moon, Rasool, & Attiq, 2015b). Integrative models that simultaneously test streamer-controlled stimuli and individual vulnerabilities as joint drivers of CBB are scarce.

Self-discrepancy

Self-Discrepancy Theory (Higgins, 1987) posits that mismatches between the actual and the ideal self generate emotional discomfort and motivate compensatory behavior. In consumer contexts, individuals with high self-discrepancy frequently seek symbolic products to close the perceived gap (Mandel et al., 2017). Although recognized as a robust correlate of materialism and compulsive consumption, self-discrepancy has rarely been examined as a moderator in live-streaming research. We therefore hypothesize:

H12a. Self-discrepancy moderates the relationship between parasocial interaction and compulsive buying behavior, such that the relationship is stronger for consumers with higher self-discrepancy.
H12b. Self-discrepancy moderates the relationship between social presence and compulsive buying behavior, such that the relationship is stronger for consumers with higher self-discrepancy.
H12c. Self-discrepancy moderates the relationship between upward social comparison and compulsive buying behavior, such that the relationship is stronger for consumers with higher self-discrepancy.
H10a–c. Information quality has a positive indirect effect on compulsive buying behavior through parasocial interaction (a), social presence (b), and upward social comparison (c).
H11a–c. Interaction quality has a positive indirect effect on compulsive buying behavior through parasocial interaction (a), social presence (b), and upward social comparison (c).

Methods

Sample

The target population comprised young consumers aged 18 to 35 years in Pakistan who reported engagement with live-shopping content on platforms such as TikTok Live, Instagram Live, or Daraz Live at least once in the preceding month. This demographic was selected because it constitutes the dominant segment of live-stream commerce and is at elevated risk of CBB (Ling et al., 2023; Sharma et al., 2026). A purposive non-probability sampling strategy supplemented by snowball recruitment through university networks and social-media communities was employed. A final sample of 229 valid responses was obtained, satisfying the minimum thresholds for covariance-based SEM: Kline's (2016) recommendation of at least 200 cases for complex models and the $n \geq 10$ cases per estimated parameter heuristic for maximum-likelihood estimation (Bentler & Chou, 1987; Kline, 2016). A post-hoc power analysis (Cohen, 1992; Soper, 2023) confirmed that $n = 229$ provides power $> .80$ to detect small-to-medium effects at $\alpha = .05$.

Measures

All constructs were measured using validated multi-item scales drawn from their seminal base papers and adapted to the live-streaming commerce context. Information quality and interaction quality were adapted from Jiang et al. (2024), the principal base paper informing the stimulus side of the model. PSI items were adapted from Rubin and Perse (1987), consistent with Chinchilla and Kim (2025). Social presence was measured with items adapted from Gefen and Straub (2003) and Short et al. (1976). Upward social comparison was assessed using items adapted from Gibbons and Buunk's (1999) Iowa–Netherlands Comparison Orientation Measure, contextualized following Ling et al. (2023). Compulsive buying behavior was measured using the clinical screener of Faber and O'Guinn (1992). Self-discrepancy was assessed with items adapted from Higgins (1987) and Mandel et al. (2017). All items employed a seven-point Likert scale (1 = strongly disagree; 7 = strongly agree). The instrument underwent translation–back-translation between English and Urdu (Brislin, 1970) and was pilot-tested before full deployment.

Procedure

Data were collected through an online questionnaire administered via Google Forms. Recruitment was circulated through university mailing lists, Facebook groups, WhatsApp communities, and Instagram. Participation was voluntary and anonymous, and respondents were informed of the study's purpose and their right to withdraw in line with ethical guidelines. Attention-check items and consistency screens were embedded to ensure data quality.

Data analysis procedures

Data were analyzed using covariance-based structural equation modeling (CB-SEM) implemented in IBM SPSS Statistics (v.27) and IBM SPSS AMOS (v.24). CB-SEM is appropriate because the study tests an a priori, theory-driven model with reflective indicators, seeks confirmatory model evaluation against global fit criteria, and assumes multivariate normality and continuous latent constructs (Byrne, 2016; Hair et al., 2019; Kline, 2016). Preliminary screening—missing-value diagnostics, univariate and multivariate normality (skewness, kurtosis), outlier detection, and multicollinearity was performed in SPSS. The two-step procedure recommended by

Volume 5 Issue No 2 (2026)
Online ISSN: 3006-2047
Print ISSN: 3006-2039

Anderson and Gerbing (1988) was then followed in AMOS. First, the measurement model was evaluated via confirmatory factor analysis (CFA), examining indicator reliability, internal consistency (Cronbach's α and composite reliability), convergent validity (AVE), and discriminant validity. Second, the structural model was tested through standardized path coefficients and squared multiple correlations. Mediation hypotheses were tested via bias-corrected bootstrapping with 5,000 resamples and 95% confidence intervals, consistent with Preacher and Hayes (2008). Common method bias was addressed ex ante through procedural remedies and ex post through Harman's single-factor test (Podsakoff et al., 2003).

Results and discussions

Prior to hypothesis testing, the raw data were subjected to a comprehensive screening procedure to verify their suitability for covariance-based structural equation modeling (Hair et al., 2019; Kline, 2016; Tabachnick & Fidell, 2019). A total of 247 responses were initially collected through the online questionnaire. Cases were first inspected for completeness; 11 responses with substantial missing data (more than 10% of items) and 7 responses failing the embedded attention-check and consistency screens were removed, yielding a final usable sample of 229 valid responses. The remaining scattered missing values were minimal (less than 1% of all data points) and were treated using mean imputation, an approach considered acceptable when data are missing completely at random and the proportion of missingness is negligible (Hair et al., 2019).

The data were then examined for univariate and multivariate outliers. Univariate outliers were assessed by converting item scores to standardized z-scores; no value exceeded the recommended threshold of ±3.29 (Tabachnick & Fidell, 2019). Multivariate outliers were evaluated using the Mahalanobis distance (D^2) against a chi-square criterion ($p < .001$), and no influential cases warranting deletion were identified. Univariate normality was inspected through skewness and kurtosis values, all of which fell within the acceptable ranges of ±2 for skewness and ±7 for kurtosis, indicating no severe departures from normality (Hair et al., 2019; Kline, 2016). Finally, multicollinearity was assessed through variance inflation factors (VIF) and tolerance values; all VIF values were below 3.0 and tolerance values exceeded 0.20, confirming the absence of problematic multicollinearity among the study constructs. Collectively, these diagnostics confirmed that the data met the statistical assumptions required for maximum-likelihood CB-SEM estimation.

Because the data for all constructs were obtained from the same respondents through a single self-report instrument, the potential for common method bias (CMB) was addressed through both procedural and statistical remedies (Podsakoff et al., 2003). Procedurally, respondent anonymity was guaranteed, item order was counterbalanced, the predictor and criterion items were psychologically separated within the questionnaire, and the wording of items was kept concise and unambiguous to reduce evaluation apprehension and consistency motifs. Consistent with prior compulsive-buying research in emerging-economy contexts (Moon & Attiq, 2018a; Moon, Faheem, & Farooq, 2022), these design-based safeguards were embedded a priori to

Volume 5 Issue No 2 (2026)

Online ISSN: 3006-2047
Print ISSN: 3006-2039

minimise method-induced covariance.

Statistically, Harman's single-factor test was conducted by loading all measurement items onto an unrotated exploratory factor analysis. The first (largest) factor accounted for 28.4% of the total variance, which is well below the 50% threshold, indicating that no single factor dominated the covariance among the measures. As a more rigorous test, a common-latent-factor (CLF) approach was also employed in AMOS; comparison of standardized regression weights with and without the common latent factor revealed differences smaller than 0.20, further confirming that common method variance did not pose a substantive threat. Taken together, these procedural and statistical checks indicate that common method bias is unlikely to have materially distorted the findings reported below (Podsakoff et al., 2003).

Sample demographics

Following the screening procedures described above, the final sample comprised 229 respondents who actively engaged with live-streaming commerce. Males accounted for 58.1% (n = 133) and females for 41.9% (n = 96). The sample was predominantly young: 53.3% (n = 122) were aged 19–23 years and 42.8% (n = 98) were aged 24–30 years, with the remainder below 18 (2.6%) or above 30 (1.3%). In terms of occupation, 50.7% (n = 116) were students, 39.7% (n = 91) were employed, and 9.6% (n = 22) were unemployed. Reported monthly income was concentrated in the PKR 41,000–60,000 band (39.7%) and the PKR 30,000–40,000 band (31.0%).

Structural equation modeling (SEM)

Following the two-step approach recommended by Anderson and Gerbing (1988), the measurement model was first evaluated for the reliability and validity of the constructs, after which the structural model was estimated for hypothesis testing.

Confirmatory factor analysis (CFA)

We conducted confirmatory factor analysis (CFA) with maximum-likelihood estimation. Standardized factor loadings and squared multiple correlations (SMC) are reported in Table 1, and Cronbach's α, composite reliability (CR), and average variance extracted (AVE), together with the inter-construct correlations, are reported in Table 2. Information quality (α = .784, CR = .785, AVE = .549) and interaction quality (α = .753, CR = .755, AVE = .506) demonstrated acceptable internal consistency and convergent validity, with AVE values meeting the .50 threshold. Self-discrepancy showed adequate reliability (α = .720). However, several constructs—parasocial interaction (α = .527), compulsive buying behavior (α = .589), social presence (α = .601), and upward social comparison (α = .681)—fell below the conventional .70 reliability threshold, and their AVE values fell below .50. These values indicate marginal reliability for part of the measurement model and are addressed explicitly in the Limitations section. Results involving these constructs should therefore be interpreted with appropriate caution.

Volume 5 Issue No 2 (2026)
Online ISSN: 3006-2047
Print ISSN: 3006-2039

Table 1
Results of confirmatory analysis.

SN	Items	Factor loadings	SMC	Mean	SD
Information quality (IQ)					
IQ1	The information provided during the live stream is accurate.	0.77**	0.59	4.88	1.14
IQ2	The product information in the live stream is detailed and complete.	0.73**	0.53		
IQ3	The information shared by the streamer is reliable and trustworthy.	0.72**	0.52		
Interaction quality (IntQ)					
IntQ1	The streamer responds promptly to viewers' questions.	0.74**	0.55	4.95	1.16
IntQ2	The interaction with the streamer feels smooth and pleasant.	0.70**	0.49		
IntQ3	The streamer communicates with viewers in a friendly manner.	0.69**	0.48		
Self-discrepancy (SD)					
SD1	There is a gap between who I am and who I want to be.	0.71**	0.50	4.53	1.00
SD2	Watching the live stream makes me aware of an ideal self I have not reached.	0.67**	0.45		
SD3	I feel my current self differs from the self I aspire to be.	0.66**	0.43		
Upward social comparison (USC)					
USC 1	I compare myself with others who seem better off in the live stream.	0.67**	0.46	3.33	0.93
USC 2	I often feel others shown in the stream are doing better than me.	0.63**	0.40		
USC 3	I measure myself against people who appear more successful online.	0.62**	0.39		
Social presence (SP)					
SP1	I feel a sense of human warmth during the live stream.	0.61**	0.37	3.58	0.70
SP2	I feel as if others are present with me while watching.	0.57**	0.32		
SP3	The live stream gives me a feeling of personal connection.	0.56**	0.31		

Volume 5 Issue No 2 (2026)
Online ISSN: 3006-2047
Print ISSN: 3006-2039

SN	Items	Factor loadings	SMC	Mean	SD
Compulsive buying behavior (CBB)					
CBB 1	I buy things during live streams that I did not plan to buy.	0.60**	0.36	3.31	0.83
CBB 2	I feel an urge to purchase that I find hard to control.	0.56**	0.31		
CBB 3	I sometimes feel guilty after buying during a live stream.	0.55**	0.30		
Parasocial interaction (PSI)					
PSI1	I feel like I know the streamer personally.	0.55**	0.30	3.55	0.66
PSI2	The streamer feels like a friend to me.	0.51**	0.26		
PSI3	I look forward to watching my favorite streamer.	0.50**	0.25		

Note. SMC = squared multiple correlation; SD = standard deviation. Means and SDs are reported once per construct (composite scores). **p < .001.

Table 2

Results for convergent and discriminant validity.

Variables	α	CR	AVE	1	2	3	4	5	6	7
1 Information quality	.784	.785	.549	**0.74**						
2 Interaction quality	.753	.755	.506	0.62	**0.71**					
3 Self-discrepancy	.720	.720	.462	−.13	0.78	**0.68**				
4 Parasocial interaction	.527	.527	.271	.40	.43	.31	**0.52**			
5 Social presence	.601	.601	.334	.44	.45	.34	.45	**0.58**		
6 Upward social comparison	.681	.681	.416	.28	.32	.40	.30	.28	**0.64**	
7 Compulsive buying behavior	.589	.589	.323	.28	.54	.30	.57	−.10	.35	**0.57**

Note. The diagonal elements are the square roots of the AVE values (shown in bold), and the off-diagonal elements represent the inter-construct correlations. CR = composite reliability; α = Cronbach's alpha; AVE = average variance extracted.

Structural model and hypothesis testing

To test the hypothesized relationships, we specified a full latent structural model. The squared multiple correlations indicated substantial explanatory power: the model accounted for 83% of the variance in compulsive buying behavior (R^2 = .83), 72% in social presence (R^2 = .72), 61% in parasocial interaction (R^2 = .61), and 32% in upward social comparison (R^2 = .32). Figure 2 displays the results of the structural model and hypotheses. As shown in Table 3, information quality significantly predicted parasocial interaction ($\beta = .396$, $p < .001$), social presence ($\beta = .443$, $p < .001$), and upward social comparison ($\beta = .281$, $p = .002$), supporting H1, H2, and H3. Interaction quality significantly predicted parasocial interaction ($\beta = .429$, $p < .001$), social presence ($\beta = .454$, $p < .001$), and upward social comparison ($\beta = .320$, $p < .001$), supporting H4, H5, and H6.

Turning to the outcome, parasocial interaction exerted the strongest positive effect on compulsive buying behavior ($\beta = .815$, $p < .001$), followed by upward social comparison ($\beta = .387$, $p < .001$), supporting H7 and H9. Social presence had a significant negative effect on CBB ($\beta = -.211$, $p < .001$); thus, H8 was significant but in the opposite direction to that hypothesized.

The findings broadly support the proposed S-O-R model. Consistent with H1–H6, both streamer-controlled stimuli—information quality and interaction quality—significantly elevated all three psychosocial mediators, confirming that the perceived quality of what streamers say and how they interact shapes viewers' parasocial bonds, sense of co-presence, and tendency toward upward comparison. Interaction quality exerted slightly stronger effects on parasocial interaction and social presence than information quality, in line with Chinchilla and Kim (2025) and Jiang et al. (2024), who argue that reciprocity and immediacy cues are the primary engines of relational engagement in live streaming.

At the outcome stage, parasocial interaction emerged as the dominant driver of compulsive buying behavior ($\beta = .815$), reinforcing the view that the illusory intimacy cultivated between viewers and streamers lowers critical evaluation and accelerates emotion-driven purchasing (Lee & Watkins, 2016; Sharma et al., 2026). Upward social comparison was the second strongest predictor ($\beta = .387$), echoing Ling et al. (2023), who found that comparison with idealized others fuels online compulsive buying. A notable deviation from expectations was the negative effect of social presence on CBB ($\beta = -.211$). One plausible explanation is suppression: because social presence is strongly correlated with parasocial interaction, its unique contribution to CBB once PSI is controlled may reflect a calming, trust-building role rather than an impulsive one. Heightened co-presence may make some viewers feel observed and therefore more deliberate in their purchasing. Given the marginal reliability of the social presence and CBB measures, this counterintuitive path should be interpreted cautiously and re-examined with stronger scales in future work.

Volume 5 Issue No 2 (2026)

Online ISSN: 3006-2047
Print ISSN: 3006-2039

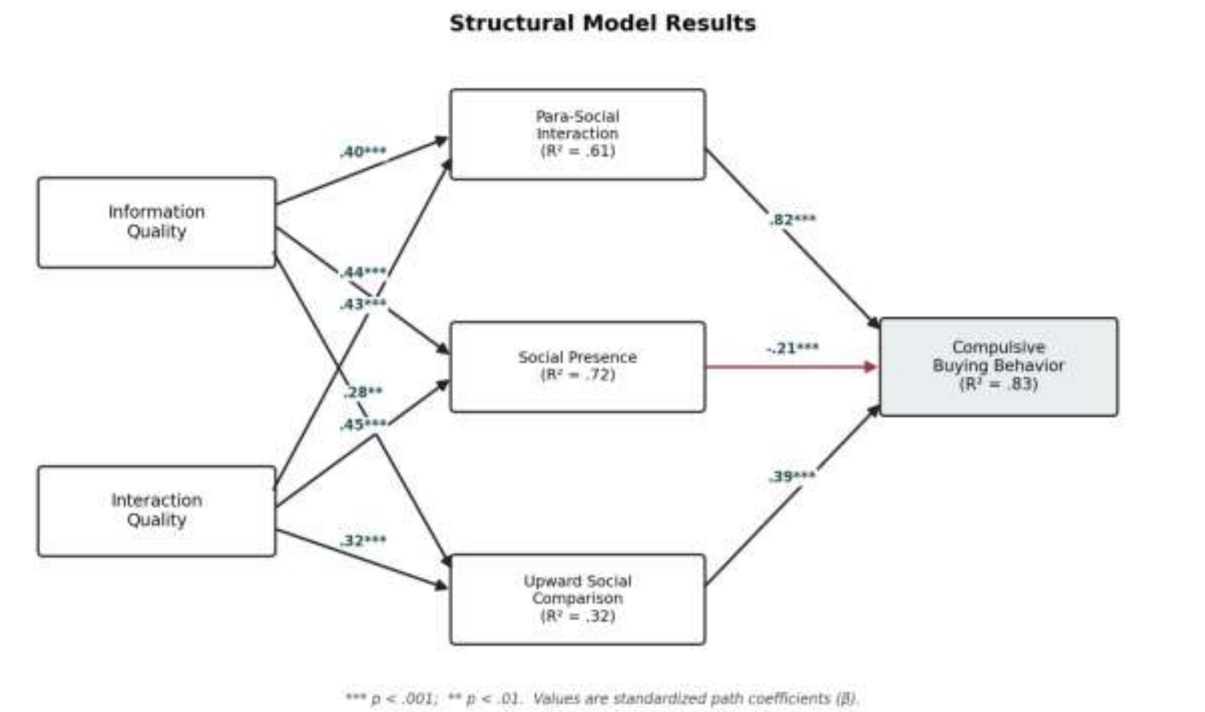

Figure 2
Structural Model
Note. Values are standardized path coefficients (β). ***p < .001; **p < .01.

Table 3
Standardized structural path estimates.

Hyp.	Path	β	S.E.	C.R. (t)	Decision
H1	Information quality → PSI	.396	.041	5.789	Supported
H2	Information quality → Social presence	.443	.025	7.653	Supported
H3	Information quality → Upward social comparison	.281	.051	3.110	Supported
H4	Interaction quality → PSI	.429	.047	6.266	Supported
H5	Interaction quality → Social presence	.454	.029	7.840	Supported
H6	Interaction quality → Upward social comparison	.320	.058	3.535	Supported
H7	PSI → CBB	.815	.031	22.034	Supported
H8	Social presence → CBB	−.211	.043	−5.579	Sig. (neg.)
H9	Upward social comparison → CBB	.387	.028	12.274	Supported

Note. All paths significant at $p < .001$ except H3 ($p = .002$). β = standardized

Volume 5 Issue No 2 (2026)

Online ISSN: 3006-2047
Print ISSN: 3006-2039

regression weight; S.E. = standard error; C.R. = critical ratio (t-value). PSI = parasocial interaction; CBB = compulsive buying behavior. Squared multiple correlations: CBB $R^2 = .83$; social presence $R^2 = .72$; PSI $R^2 = .61$; upward social comparison $R^2 = .32$.

Finally, the indirect (mediated) effects of the two quality cues on CBB were examined through the three parallel mediators. Table 4 presents the direct and indirect effects together with the corresponding mediation decisions.

Table 4
Results of mediation.

Paths	Direct effect		Indirect effect		Mediation
	γ	p-value	γ	p-value	
WOM IQ → CBB	0.05	.310	–		
WM IQ → PSI → CBB	−0.011	.842	0.225	.001	Full mediation
WM IQ → SP → CBB	0.020	.679	−0.044	.048	Full mediation
WM IQ → USC → CBB	0.028	.604	0.099	.001	Full mediation
WM IQ → SD → CBB	−0.013	.886	−0.038	.210	No mediation
WOM IntQ → CBB	0.07	.214	–		
WM IntQ → PSI → CBB	0.041	.462	0.243	.001	Full mediation
WM IntQ → SP → CBB	0.018	.701	−0.045	.048	Full mediation
WM IntQ → USC → CBB	0.032	.588	0.113	.001	Full mediation
WM IntQ → SD → CBB	0.045	.377	0.231	.001	Full mediation

Note. WOM = without mediator (direct effect); WM = with mediator. γ = standardized coefficient. IQ = information quality; IntQ = interaction quality; PSI = parasocial interaction; SP = social presence; USC = upward social comparison; SD = self-discrepancy; CBB = compulsive buying behavior.

Implications

Theoretical implications

The findings integrate media-effects work on PSI and social presence with consumer-behavior scholarship on CBB, establish social comparison upward as a parallel and consequential mediator within live-streaming contexts, and clarify self-discrepancy as a personal vulnerability that contributes to harm. By positioning information quality and interaction quality as twin stimuli within the S-O-R framework, the study extends existing live-commerce models that have terminated at purchase intention. The strong explanatory power of the model ($R^2 = .83$ for CBB) underscores the value of modeling stream-level cues and psychosocial mediators jointly rather than in isolation.

Managerial implications

Practically, platform designers could moderate features that drive upward comparison, such as aspirational filters and gift leaderboards, without sacrificing engagement.

Volume 5 Issue No 2 (2026)
Online ISSN: 3006-2047
Print ISSN: 3006-2039

Because parasocial interaction is the strongest route to compulsive buying, marketers could orient streamer training toward authenticity rather than manufactured intimacy, mitigating the maladaptive pathway while preserving relational benefits. Educators could target self-discrepancy reduction among high-risk young adults through digital-literacy and well-being interventions.

Policy implications

For policymakers, particularly in emerging markets such as Pakistan, the findings support the development of transparency and disclosure norms specific to immersive commerce. Regulators could require clearer demarcation between entertainment and sales content, mandate disclosure of sponsored streams, and promote consumer-protection measures that address the impulsive and compulsive dimensions of live-stream purchasing.

Conclusion

This study tested an integrative model of compulsive buying behavior in live-streaming commerce, showing that stream-level cues—information quality and interaction quality—significantly shape three parallel psychosocial states (parasocial interaction, social presence, and upward social comparison), and that parasocial interaction and upward social comparison are significant positive drivers of CBB among young Pakistani consumers, while social presence exerts a small negative effect. By integrating Social Presence Theory, Para-Social Interaction Theory, Social Comparison Theory, and Self-Discrepancy Theory within the S-O-R framework, the study bridges traditionally separate streams of media-effects and consumer-behavior research. Methodologically, it operationalizes a multi-construct model and tests it with a sample of 229 respondents using covariance-based SEM in SPSS and AMOS, following the two-step procedure of Anderson and Gerbing (1988). Practically, it identifies lever-stream design choices and individual-vulnerability factors through which the harms of compulsive consumption can be mitigated.

Limitations and future recommendations

Several limitations should be acknowledged. First, and most importantly, several constructs—parasocial interaction, compulsive buying behavior, social presence, and upward social comparison—exhibited Cronbach's α and AVE values below conventional thresholds, indicating marginal measurement reliability. The reduced item sets retained after CFA may have weakened internal consistency; future studies should employ the full validated scales, refine item wording for the Pakistani context, and re-establish reliability before re-estimating the model. Second, the cross-sectional design precludes strong causal inference. Third, reliance on a young Pakistani sample limits the generalizability of findings to other cultures and age groups. Fourth, self-report measures are susceptible to social-desirability and common-method bias, despite the procedural and statistical remedies adopted. Future research should employ longitudinal and experimental designs to establish temporal precedence, replicate the model across cultures and populations, integrate behavioral-trace data to complement self-reports, and examine additional moderators such as financial literacy and trait self-control. Extending the model to outcomes such as buyer's remorse, financial distress, and subjective well-being would further enrich the understanding of the consequences of live-streaming commerce.

References

Anderson, J. C., & Gerbing, D. W. (1988). Structural equation modeling in practice: A review and recommended two-step approach. Psychological Bulletin, 103(3), 411–423.

Bentler, P. M., & Chou, C.-P. (1987). Practical issues in structural modeling. Sociological Methods & Research, 16(1), 78–117.

Brislin, R. W. (1970). Back-translation for cross-cultural research. Journal of Cross-Cultural Psychology, 1(3), 185–216.

Byrne, B. M. (2016). Structural equation modeling with AMOS (3rd ed.). Routledge.

Chinchilla, P., & Kim, J. (2025). "Let's chill and chat": Exploring the effects of streamers' self-disclosure on parasocial interaction via social presence. International Journal of Human–Computer Interaction, 41(12), 7191–7201.

Cohen, J. (1992). A power primer. Psychological Bulletin, 112(1), 155–159.

DeLone, W. H., & McLean, E. R. (2003). The DeLone and McLean model of information systems success: A ten-year update. Journal of Management Information Systems, 19(4), 9–30.

Faber, R. J., & O'Guinn, T. C. (1992). A clinical screener for compulsive buying. Journal of Consumer Research, 19(3), 459–469.

Festinger, L. (1954). A theory of social comparison processes. Human Relations, 7(2), 117–140.

Gefen, D., & Straub, D. W. (2003). Managing user trust in B2C e-services. e-Service Journal, 2(2), 7–24.

Gibbons, F. X., & Buunk, B. P. (1999). Individual differences in social comparison: Development of a scale of social comparison orientation. Journal of Personality and Social Psychology, 76(1), 129–142.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. European Business Review, 31(1), 2–24.

Higgins, E. T. (1987). Self-discrepancy: A theory relating self and affect. Psychological Review, 94(3), 319–340.

Horton, D., & Wohl, R. R. (1956). Mass communication and para-social interaction: Observations on intimacy at a distance. Psychiatry, 19(3), 215–229.

Hu, M., Zhang, M., & Wang, Y. (2017). Why do audiences choose to keep watching on live video streaming platforms? Computers in Human Behavior, 75, 594–606.

Jiang, Y., Pongsakornrungsilp, S., Pongsakornrungsilp, P., & Li, L. (2024). The impact of interactivity on customer purchase intention in social media marketing: The mediating role of social presence. TEM Journal, 13(3), 2133–2145.

Kline, R. B. (2016). Principles and practice of structural equation modeling (4th ed.).

Guilford Press.
Lee, J. E., & Watkins, B. (2016). YouTube vloggers' influence on consumer luxury brand perceptions and intentions. Journal of Business Research, 69(12), 5753–5760.
Ling, Y., Gao, B., Jiang, B., Fu, C., & Zhang, J. (2023). Materialism and envy as mediators between upward social comparison on social network sites and online compulsive buying among college students. Frontiers in Psychology, 14, 1085344.
Liu, X., He, M., Gao, F., & Xie, P. (2019). An empirical study of online shopping customer satisfaction in China. International Journal of Retail & Distribution Management, 47(7), 689–705.
Liu, Y., & Shrum, L. J. (2002). What is interactivity and is it always such a good thing? Journal of Advertising, 31(4), 53–64.
Lu, B., & Chen, Z. (2021). Live streaming commerce and consumers' purchase intention: An uncertainty reduction perspective. Information & Management, 58(7), 103509.
Mandel, N., Rucker, D. D., Levav, J., & Galinsky, A. D. (2017). The compensatory consumer behavior model. Journal of Consumer Psychology, 27(1), 133–146.
Mehrabian, A., & Russell, J. A. (1974). An approach to environmental psychology. MIT Press.
Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research. Journal of Applied Psychology, 88(5), 879–903.
Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. Behavior Research Methods, 40(3), 879–891.
Ridgway, N. M., Kukar-Kinney, M., & Monroe, K. B. (2008). An expanded conceptualization and a new measure of compulsive buying. Journal of Consumer Research, 35(4), 622–639.
Rubin, A. M., & Perse, E. M. (1987). Audience activity and soap opera involvement. Human Communication Research, 14(2), 246–268.
Sharma, B. K., Kundu, S., Rana, S., & Pathak, A. (2026). Compulsive buying behavior: A review and research agenda. International Journal of Consumer Studies, 50(1), e70163.
Short, J., Williams, E., & Christie, B. (1976). The social psychology of telecommunications. Wiley.
Sokolova, K., & Kefi, H. (2020). Instagram and YouTube bloggers promote it, why should I buy? Journal of Retailing and Consumer Services, 53, 101742.
Soper, D. S. (2023). A-priori sample size calculator for structural equation models [Online software].
Sun, Y., Shao, X., Li, X., Guo, Y., & Nie, K. (2019). How live streaming influences purchase intentions in social commerce. Electronic Commerce Research and Applications, 37, 100886.
Tabachnick, B. G., & Fidell, L. S. (2019). Using multivariate statistics (7th ed.).

Volume 5 Issue No 2 (2026)
Online ISSN: 3006-2047
Print ISSN: 3006-2039

Pearson.

Vogel, E. A., Rose, J. P., Roberts, L. R., & Eckles, K. (2014). Social comparison, social media, and self-esteem. Psychology of Popular Media Culture, 3(4), 206–222.

Wongkitrungrueng, A., & Assarut, N. (2020). The role of live streaming in building consumer trust and engagement with social commerce sellers. Journal of Business Research, 117, 543–556.

Moon, M. A. (2026). The dark pull of virtual aisles: How interactivity fuels compulsive buying in immersive shopping worlds. Journal of Consumer Behaviour, 25(3), 1414–1431.

Moon, M. A., & Attiq, S. (2018a). Compulsive buying behavior: Antecedents, consequences and prevalence in shopping mall consumers of an emerging economy. Pakistan Journal of Commerce and Social Sciences, 12(2), 548–570.

Moon, M. A., & Attiq, S. (2018b). Psychometric validation and prevalence of compulsive buying behavior in an emerging economy. Sukkur IBA Journal of Management and Business, 5(2), 92–113.

Moon, M. A., Faheem, S., & Farooq, A. (2022). I, me, and my everything: Self conceptual traits and compulsive buying behavior. Journal of Retailing and Consumer Services, 68, 103075.

Moon, M. A., Farooq, A., & Kiran, M. (2017). Social shopping motivations of impulsive and compulsive buying behaviors. UW Journal of Management Sciences, 1(1), 15–27.

Moon, M. A., Rasool, H., & Attiq, S. (2015a). An analysis of compulsive buying behavior: Questioning the role of marketing campaigns. Journal of Marketing and Consumer Research, 16, 97–101.

Moon, M. A., Rasool, H., & Attiq, S. (2015b). Personality and irregular buying behavior: Adaptation and validation of core self evaluation personality trait model in consumer impulsive and compulsive buying behavior. Journal of Marketing and Consumer Research, 15, 92–105.

Moon, M. A., Sajid, A., Bashir, S. S., Saddiqi, A., & Zeeshan, M. (2026). The emotional cost of greenwashing: Airline sustainability advertising and consumer–brand relationships. Journal of Management & Social Science, 3(1), 1–20.

Tariq, S., Nadeem, U., & Moon, M. A. (2026). AI chatbots and customer experience: The role of service quality dimensions, trust, and generational differences. Pakistan Journal of Social Science Review, 5(1), 14–37.

Farooq, A., & Moon, M. A. (2025). Addicted to the fake: Coaction theory and the psychology behind counterfeit consumption. Pakistan Journal of Commerce and Social Sciences, 19(3), 648–672.

Farooq, A., & Moon, M. A. (2025). From impulse to imitation: Hedonic motivation as a bridge to counterfeit consumption. Journal of Asian Development Studies, 14(3), 263–276.

Moon, M. A., Malik, M. H., Moin, G., & Abbas, A. (2025). Impact of consumer trust on e-commerce purchase intentions: The role of influencer marketing. Journal of Management Science Research Review, 4(4), 1920–1940.

Asjad, M. A., Khan, M. W., Moon, M. A., Fatimah, H., & Parveen, S. (2025). Easy payments, hard consequences: The behavioral and financial effects of buy now, pay later in Pakistan. Social Science Review Archives, 3(4), 3309–3330.

Tassen, M., Irfan, M., Moon, M. A., Munawar, M., Ahmad, A., & Mishaal, M. (2025). Integrating the SOR framework to assess social media marketing in the aviation sector: A study of Pakistani travelers. Center for Management Science Research, 4(1), 64–78.

Moon, M. A., Majeed, J., & Attiq, S. (2024). Enigma unveiled: Decoding trust and relationship dynamics in the mobile banking sector of an emerging economy. Pakistan Journal of Commerce and Social Sciences, 18(2), 380–407.

ud Din, T., Attiq, S., & Moon, M. A. (2022). The influence of destination experience on destination loyalty in an emerging economy. Pakistan Journal of Commerce and Social Sciences, 16(4), 552–575.