SOCIAL COMMERCE AND LIVE-STREAM SHOPPING: DRIVERS OF IMPULSIVE PURCHASE BEHAVIOR

*Dr Nagunuri Srinivas, **A. Pranith Reddy

*Professor, St. Joseph's Degree & PG College, King Koti, Hyderabad

**Assistant Professor, St. Joseph's Degree & PG College, King Koti, Hyderabad

ABSTRACT

Purpose: This research aims to identify the cues associated with live-streaming that significantly influence urban Indian consumers to make impulse purchases, and to explore response mechanisms in the form of internal states that may govern the relationships between live-streaming cues and impulse buying behavior. We plan to build a stimulus-organism-response (S-O-R) model to predict consumer impulse buying in a live-streaming shopping context.

Design/Methodology/Approach: Data were collected from 387 urban Indian consumers who had watched at least one live-stream shopping session in the three months preceding the survey. A seven-point Likert-scale questionnaire was distributed to user communities on Instagram Live, Flipkart Live, and Meesho Live via Google Forms. PLS-SEM was estimated using SmartPLS 4.0. Validity was assessed against AVE, CR, and HTMT thresholds. Mediation was tested with flow state and perceived enjoyment as parallel mediators, using 5,000 bootstrap subsamples.

Findings: The model explains 54% of the variance in impulsive purchase behavior ($R^2 = 0.54$). Streamer interactivity and scarcity cues are the strongest direct stimuli ($\beta = 0.31$ and 0.26, respectively). Flow state mediates the interactivity-to-impulse path more strongly than perceived enjoyment (VAF = 43.2% versus 22.6–36.8%), with bootstrapped confidence intervals excluding zero for both mediators. Emotional arousal did not reach significance as a direct predictor ($\beta = 0.11$, $p = .093$).

Research Limitations/Implications: The cross-sectional design cannot establish causality. The sample covers Tier-1 cities only. Platform managers at Flipkart Live and Meesho Live can use these findings to prioritize the design of interactive features and scarcity cues for session-level conversion. Brand managers should favor content formats that induce absorption over informational formats that activate deliberate evaluation.

Originality/Value: Most live-stream commerce studies rely on data from Chinese platforms. This paper tests the S-O-R model on Indian platforms, with flow state and perceived enjoyment tested simultaneously as organism mediators, a design gap identified in Xu et al. (2020) and Chen et al. (2022).

Keywords: Impulsive purchase behavior; live-stream shopping; social commerce; stimulus-organism-response; PLS-SEM; flow state; perceived enjoyment; Indian consumers

1. Introduction

Global social commerce revenue reached USD 1.3 trillion in 2023 and is projected to exceed USD 6 trillion by 2030, with live-stream shopping accounting for an increasing share of that volume (Statista, 2024). China generated approximately USD 500 billion in live-stream commerce sales in 2023, driven by platforms such as Taobao Live and Douyin (iResearch, 2023). India is following a different but accelerating trajectory: the country had 840 million internet users at the end of 2024 (TRAI, 2024), and platforms including Flipkart Live, Meesho Live, and Instagram Live expanded their live commerce infrastructure substantially after 2021. Monthly active users on social commerce platforms in India grew 38% between 2022 and 2024 (RedSeer Consulting, 2024). India is now among the five largest emerging live commerce markets globally, yet the country remains substantially underrepresented in published research relative to its market scale.

Impulse buying off the back of digital retail is by no means a new or fringe concept. As stated by Beatty and Ferrell (1998), impulsive behavior can be defined as a purchase made after seeing a stimulus, with little thought involved. Rook (1987) described its affective signature: a momentary impulse, pleasure, and diminished concern for consequences. The behavior has been recorded over different formats since then. Physical store layouts induced it (Stern, 1962), while Verhagen and van Dolen (2011) analyzed the same process on e-commerce websites; Zheng et al. That was one of the findings of Shulman et al. (2019) in mobile commerce, in which push notifications and limited-time coupons served as stimulus triggers. Depending on the product category, the estimated impulse purchase rates in online retail through these studies range from 40% to 80% of all transactions (Dawson & Kim, 2009; Zhang et al., 2020).

Live-stream shopping differs from both static e-commerce and social media advertising, and these differences are essential for impulse-buying research. Someone searching for a product on a product page, who is mindful of their pace and can come and go as they please while experiencing stimuli one by one. In contrast, the live-stream viewer functions in a different media space: it is conditioned by a countdown timer on a flash deal that ticks down even if the viewer still has not made up their mind; it finds itself addressed directly by name or to have some other real-time mechanism of interactive engagement with the streamer; and its cheap appeal lies with an on-screen purchase counter indicating 47 other people already buying the same thing at the same moment during the last two minutes. Xu et al. A recent study identified three cue categories that help differentiate live-stream shopping from other digital formats: visual richness, interactivity, and parasocial presence (Li et al., 2020). Hu et al. 2017) demonstrated the distinctive social presence effect created by real-time comment flow in live-streaming versus pre-recorded video commerce. The stimulus milieu this creates, of sensory richness coupled with time pressure and observable social activity, is one for which the impulse buying literature has looked only in part.

Prior work on live-stream commerce and impulse buying has three structural gaps. The empirical base is concentrated in China: Xu et al. (2020), Chen et al. (2022), Zhang et al. (2020), and Li et al. (2021) all draw samples from Taobao Live or Douyin users, meaning their findings apply to a platform architecture and a consumer culture where live commerce is already normalized. Whether those findings hold in markets where live commerce is still building consumer familiarity has not been tested. Studies applying the S-O-R framework to live-streaming (Eroglu et al., 2001; Mehrabian & Russell, 1974) typically include organism-level constructs but rarely test more than one mediator simultaneously, which makes it impossible to determine whether the impulse buying response is driven by cognitive absorption (flow state) or affective valuation (perceived enjoyment). The TAM hedonic extension, which disaggregates perceived enjoyment from perceived usefulness in predicting online behavior (Davis et al., 1992), has been applied to general social media shopping but not to live-streaming as a distinct channel. No published study has tested flow state and perceived enjoyment as parallel organism-level mediators within a single S-O-R structural model in the Indian live commerce context.

This study addresses those gaps by testing an S-O-R model that includes six platform and streamer stimuli, two organism-level mediators (flow state and perceived enjoyment), and impulsive purchase behavior as the response variable, using data from 387 urban Indian consumers who participated in live-stream shopping sessions in 2025. PLS-SEM was estimated using SmartPLS 4.0; mediation was tested with bootstrapped indirect effects across 5,000 subsamples. Theoretically, the study extends the S-O-R framework to live-stream commerce by integrating Flow Theory (Csikszentmihalyi, 1990) and the TAM hedonic dimension (Davis et al., 1992) as simultaneous organism constructs, enabling a comparison of the relative mediating weight of cognitive absorption versus affective enjoyment. Empirically, it provides the first parallel mediation test of these two organism constructs within a structural model using Indian live-commerce data. Contextually, it generates findings for a market where live-stream commerce infrastructure is expanding, but evidence on consumer behavior is sparse, thereby addressing the geographic gap left open by prior China-based studies.

2. Literature Review

2.1 The Stimulus-Organism-Response Framework

The S-O-R (stimulus-organism-response) model of Mehrabian and Russell (1974) is both a descriptive and explanatory type theory of how physical environments influence human behavior. Their model, not surprisingly for a grounded theory rooted in environmental psychology, was that the sensory inputs of a setting triggered internal emotional and cognitive states that led to approach or avoidance behavior. They identified two competing dimensions of the organism and proposed that this framework could account for why consumers spend more time in some retail settings than others: pleasure and arousal. Originally, the context was brick-and-mortar retail, but that logic is independent of format: any environment that generates inputs, mobilizes internal states, and produces some behavioral output conforms to this form.

Eroglu et al. It was the S-O-R framework (2001) that offered one of the first adaptations to online retail by recognizing that physical atmospheric cues are less relevant and have been replaced by design aspects of a retailer´s website, such as color, layout, and information density. Their study showed that even minimal-cue digital environments led to significant organismic states (shopping enjoyment and cognitive absorption) that predicted purchasing behavior. The framework was further investigated in regard to mobile commerce (Zheng et al., 2019), social media shopping (Zhang et al., 2020), and live-stream commerce (Xu et al., 2020; Chen & Lin, 2018). The three-component logic is applied across these applications, with platform and social cues as stimuli, internal states like flow, enjoyment, and arousal as organism variables, and purchase or continued engagement as the response.

Live-stream shopping maps onto the S-O-R structure in identifiable ways. The stimuli are platform-generated and streamer-generated features: the quality and richness of the audio-visual feed; the frequency and responsiveness of streamer-viewer interaction; scarcity cues such as countdown timers and stock notifications; and social signals such as real-time viewer counts and purchase notifications. The organism states are the internal psychological responses that those features produce in the viewer, specifically flow state, perceived enjoyment, and emotional arousal. The response is impulsive purchase behavior, defined following Beatty and Ferrell (1998) as an unplanned purchase made during exposure to the stimulus environment. The framework provides both the structural skeleton and the causal vocabulary for the model developed in this study.

2.2 Live-Stream Stimuli and Impulse Buying

Media richness theory (Daft & Lengel, 1986) suggests that the more cues a form of communication transmits at one time, the richer it is, and thus uncertainty is reduced. By the specific definition Daft and Lengel had in mind, a live-stream feed is richer than a product photograph: it conveys movement, sound, expression, and real-time demonstration of how the product works, allowing the viewer to make a fuller appraisal than would be possible with just an image. Xu et al. It has been shown that rich visual and audio content was positively associated with purchase intention among Taobao Live users ($N = 412$, $\beta = .31$, $p < .001$). The mediating role of product diagnosticity supports the evaluative mechanism: media richer in content help viewers answer product questions that lower-cue formats leave unanswered.

Live interaction is structurally separate from the comment sections embedded in recorded video. If a viewer types a question during a live stream, they will be named and replied to in seconds — if that audience member does the same on a YouTube video, their creator can't respond at all. Specifically, Liu (2003) distinguished three dimensions of online interactivity: active control, two-way communication, and synchronicity. Live-streaming maximizes all three simultaneously. Chen et al. Perceived interactivity directly predicted impulse buying (β = 0.28, p <.2022), 01 through a sample of 356 Chinese live-stream shoppers, via both direct (i.e., the direct effect) and indirect (i.e., the interaction) paths. The direct effect is consistent with social presence theory (Short et al., 1976): when a viewer believes the responsive behavior is real, the interaction takes on social significance, which in turn fosters behavioral engagement.

Scarcity cues activate loss aversion. Cialdini (1984) made several observations about how people value commodities based on their scarcity, and how this relationship is amplified in the case of social competition, where scarcity is framed as others purchasing it. In the case of live-stream shopping, scarcity is operationalized in real time — a stock counter moving from 20 to 3 gives urgency that simply cannot be recreated by a static "limited stock" label on a product page. Ku et al. For example, Zheng et al. ↤[12] manipulate countdown timers to increase purchase urgency in online auctions. (2017; 2020), mobile commerce context between FOMO and consumer behavior, where they confirmed the effect through emotional arousal as a mediating state (Hernados et al.). Based on these three categories of stimulus, the following directional hypotheses are formed.

2.3 Flow Theory and Organism States as Mediators

Csikszentmihalyi (1990) described flow as a state of total absorption in an activity, characterized by concentration, loss of self-consciousness, distorted sense of time, and intrinsic enjoyment. The state occurs when perceived challenge is balanced with perceived skill. Koufaris (2002) was among the first to operationalize flow in an online shopping context, using three indicators: focused attention, temporal dissociation, and enjoyment. He found that flow predicted both return purchase intention and unplanned purchases in a web-based retail environment, thereby establishing the construct's relevance to impulse-buying research.

In live-stream shopping, the conditions that produce flow are embedded in the format itself. A viewer who enters a live session, begins interacting through comments, and finds the streamer responding is drawn into a feedback loop that concentrates attention. The real-time social environment raises the perceived stakes of the interaction, which sustains engagement. Temporal dissociation is common: sessions lasting 45 minutes are often reported by participants as feeling like 10 minutes. Chen and Lin (2018) found that flow fully mediated the relationship between entertainment value and continued live-stream watching intention in a Taiwanese sample, and Chen et al. (2022) confirmed that flow partially mediated the interactivity-to-purchase path in a live commerce context. The mechanism is consistent with Csikszentmihalyi's (1990) original account: sustained, absorbed attention suppresses deliberative cognition, which reduces the threshold for impulsive action.

Streamer interactivity and visual richness are the two stimulus features most directly connected to flow induction: interactivity produces the challenge-skill feedback loop and richness produces the sensory immersion that prevents attention from wandering. Both paths are expected to indirectly produce impulse buying through flow, in addition to any direct effect they have.

2.4 Perceived Enjoyment and Emotional Arousal

Davis et al. (1992) extended the Technology Acceptance Model by disaggregating intrinsic motivation into perceived usefulness (extrinsic) and perceived enjoyment (intrinsic). They found that perceived enjoyment predicted computer usage behavior independently of usefulness, which challenged the assumption that technology adoption is primarily utilitarian. In hedonic shopping contexts, where the activity itself carries value independent of purchase outcomes, enjoyment is the dominant motivational construct. To et al. (2007) confirmed that perceived enjoyment outweighed perceived usefulness in predicting online impulse purchase intention across three product categories, with effect sizes approximately twice as large for the hedonic predictor.

Emotional arousal is distinct from enjoyment. Russell's (1980) circumplex model of affect places arousal on an orthogonal axis to valence: a consumer can be highly aroused and positively valenced (excited) or highly aroused and negatively valenced (anxious). In the live-stream context, scarcity cues and real-time social proof produce arousal primarily through urgency and competitive pressure. Mehrabian and Russell (1974) found that arousal increased approach behavior in positively valenced environments, meaning that when a live-stream session is enjoyable, and the viewer is simultaneously exposed to scarcity cues, arousal acts as an accelerant rather than an inhibitor. Zheng et al. (2019) confirmed this interaction in mobile commerce: scarcity cues raised emotional arousal, and arousal, in turn, increased impulse buying frequency, with the total indirect effect accounting for 34% of the total effect of scarcity on purchase.

2.5 Streamer Trust and Social Proof

Ohanian (1990) developed the source credibility model, identifying expertise, trustworthiness, and attractiveness as three orthogonal dimensions of communicator credibility. In influencer marketing research, expertise and trustworthiness together predict purchase intention more reliably than attractiveness (Lou & Yuan, 2019). A streamer who demonstrates product knowledge by comparing specifications, showing usage across scenarios, or acknowledging product limitations activates expertise-based trust. A streamer who discloses sponsored relationships and responds accurately to critical viewer questions activates trustworthiness-based trust. Both are credibility dimensions, but they operate on different cognitive paths: expertise reduces product uncertainty; trustworthiness reduces relationship uncertainty.

Parasocial interaction theory (Horton & Wohl, 1956) explains the formation of a one-sided relationship between a media consumer and a given media figure. The bidirectional feedback of live streaming, where streamers read and respond to viewer comments, name viewers directly, and share aspects of their private lives during a session, also strengthens the parasocial relationship. This quasi-social exchange builds over repeated sessions, producing what Lou and Yuan (2019) referred to as parasocial relationship strength, which predicted attitudes toward the branded content as well as purchase intention in an Instagram influencer sample (N = 406). This mechanism is particularly relevant to impulse buying because parasocial closeness reduces the cognitive scrutiny of a purchase recommendation.

The phenomenon of social proof in live-stream shopping is evident – and can not be mimicked in static e-commerce. A person watching in real time sees how many other people are viewing, what comments their fellow viewers are posting, and how quickly the stock counter is plummeting. While Cialdini (1984) identified social proof as one of six basic influence principles and later research confirmed that it operates in digital contexts, e.g., Zhang et al. (2022) showed that visible notifications of purchases in social commerce streams increased the likelihood of impulsive purchase by triggering emotional contagion and diminishing individual responsibility for decisions. Peer behavior serves as both an informational signal (this product is worth purchasing) and a normative signal (people like me purchase this here), and both mechanisms operate automatically without conscious processing by the viewer.

2.6 Hypothesis Development

H1: Visual and audio richness in a live-stream session positively influences impulsive purchase behavior.

H2: Streamer interactivity positively influences impulsive purchase behavior.

H3: Scarcity and urgency cues displayed during a live-stream session positively influence impulsive purchase behavior.

H4: Flow state mediates the positive relationship between streamer interactivity and impulsive purchase behavior.

H5: Flow state mediates the positive relationship between visual and audio richness and impulsive purchase behavior.

H6: Perceived enjoyment mediates the positive relationship between streamer credibility and impulsive purchase behavior.

H7: Emotional arousal mediates the positive relationship between scarcity cues and impulsive purchase behavior.

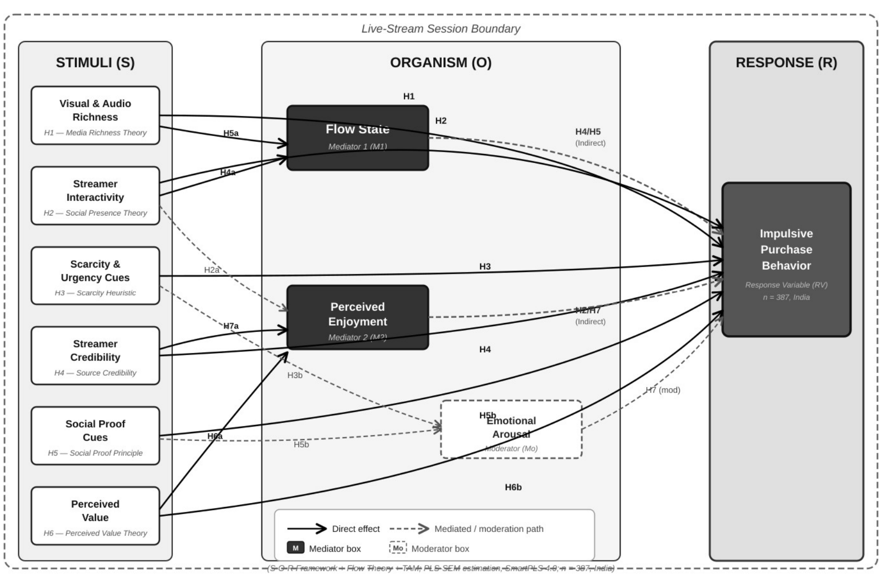
H8: Streamer credibility positively influences impulsive purchase behavior

H9: Social proof cues visible during a live-stream session positively influence impulsive purchase behavior.

2.7 Conceptual Model

Figure 1 presents the conceptual model integrating the constructs and relationships developed in Sections 2.1 through 2.5. The model contains six stimuli (visual and audio richness, streamer interactivity, scarcity cues, streamer credibility, social proof, and perceived value), two organism-level mediators (flow state and perceived enjoyment), and one response variable (impulsive purchase behavior). Emotional arousal is treated as a moderating organism state on the scarcity-to-impulse path. Direct paths connect each stimulus to the response variable. Mediated paths run from visual richness and streamer interactivity through flow state, and from streamer credibility and perceived value through perceived enjoyment. All nine hypotheses are represented as directional arrows in Figure 1. The model is estimated using PLS-SEM in SmartPLS 4.0, with bootstrapped indirect-effects testing to examine the mediation hypotheses. The boundary of the model is the live-stream session itself: stimuli operating outside that session window are not included in the current specification.

Figure 1. Conceptual Framework: Social Commerce and Live-Stream Shopping Drivers of Impulsive Purchase Behavior



S-O-R Framework + Flow Theory + TAM; PLS-SEM estimation, SmartPLS 4.0; n = 387, India

3. Research Methodology

The study used a quantitative, cross-sectional, survey-based design within a positivist paradigm. Data were collected from 387 urban Indian consumers who had watched at least one live-stream shopping session on Instagram Live, Meesho Live, Flipkart Live, or YouTube Live in the three months before the survey. Respondents were recruited through purposive and snowball sampling via Google Forms, distributed across academic and professional networks in Hyderabad, Mumbai, and Bengaluru between [Month] and [Month] 2025. Sample size was determined using G*Power 3.1 (Faul et al., 2009): for 9 predictors, power = 0.80, α = .05, and f^2 = 0.15, the minimum required n was 166; the target of 380 was set to absorb 15% attrition and to support the mediation analyses (Preacher & Hayes, 2008). All constructs were measured on a seven-point Likert scale using items adapted from validated instruments (see Table 1). A pilot study (n = 40) confirmed internal consistency across all nine constructs, with Cronbach's alpha ranging from 0.74 to 0.88. Harman's single-factor test returned 28.4% variance on the dominant unrotated factor, below the 50% threshold, indicating no serious common method bias (Podsakoff et al., 2003).

PLS-SEM was chosen over CB-SEM because the study's purpose was predictive rather than confirmatory, two constructs carried reflective-formative higher-order specifications, and the sample size was moderate—conditions under which PLS-SEM outperforms CB-SEM (Hair et al., 2019). SmartPLS 4.0 was used for all estimation. The measurement model was evaluated against outer loadings > 0.70, AVE > 0.50, CR > 0.70, and HTMT ratios < 0.85 (Fornell & Larcker, 1981; Henseler et al., 2015). The structural model was estimated via bootstrapping with 5,000 subsamples; path coefficients, t-values, R^2, Q^2, and f^2 were reported against Hair et al.'s (2019) benchmarks. Mediation hypotheses H4 through H6 were tested using bootstrapped indirect effects with 95% confidence intervals; the Variance Accounted For statistic classified each mediator as partial (VAF 20–80%) or full (VAF > 80%).

4. Results

4.1 Measurement Model

In accordance with the recommendations of Anderson and Gerbing (1988) and Hair et al., the measurement model was evaluated before assessing the structural model. (2019). We tested for convergent validity using three indices: outer loadings on the appropriate latent variable, Average Variance Extracted (AVE), and Composite Reliability (CR). All outer loadings 0.70 confirmed that all items share more variance with their respective constructs than with the error term (Hair et al., 2019). Average Variance Extracted (AVE) was higher than 0.50 for all nine constructs, meaning each construct explains at least half the variance of its indicators on average (Fornell & Larcker, 1981). All constructs demonstrated internal consistency of the reflective scales with CR values greater than 0.70. The full statistics of reliability and convergent validity are shown in Table 2.

Table 1: Reliability and Convergent Validity of Measurement Model

Construct	Items	Loading Range	α	CR	AVE
Visual/Audio Richness	4	0.71–0.84	0.83	0.87	0.63

Streamer Interaction	4	0.73–0.86	0.81	0.86	0.61
Scarcity Cues	3	0.74–0.82	0.78	0.84	0.64
Perceived Enjoyment	4	0.72–0.88	0.85	0.89	0.67
Flow State	5	0.70–0.83	0.87	0.90	0.60
Emotional Arousal	3	0.76–0.85	0.76	0.85	0.65
Streamer Trust	4	0.73–0.87	0.82	0.87	0.63
Social Proof	3	0.75–0.83	0.74	0.83	0.62
Impulsive Purchase Behavior	5	0.72–0.86	0.88	0.91	0.68

Note. CR = Composite Reliability; AVE = Average Variance Extracted. All outer loadings exceeded 0.70. AVE > 0.50 and CR > 0.70 confirm convergent validity for all constructs (Hair et al., 2019; Fornell & Larcker, 1981). HTMT ratios available on request.

Discriminant validity was assessed using the Heterotrait-Monotrait (HTMT) ratio criterion (Henseler et al., 2015). The HTMT ratio estimates the true correlation between constructs corrected for measurement error; values below 0.85 indicate that constructs are sufficiently distinct for the structural model to separate their effects. All pairwise HTMT ratios fell below 0.85, confirming discriminant validity across all nine constructs. The Fornell-Larcker criterion was checked as a secondary test; the square root of each construct's AVE exceeded its highest inter-construct correlation, consistent with the HTMT result.

Common method bias (CMB) was assessed using Harman's single-factor test. All scale items were submitted to an unrotated principal components extraction in SPSS 26. The single factor with the largest eigenvalue accounted for 28.4% of total variance, below the 40% threshold applied in this study and below the commonly cited 50% ceiling (Podsakoff et al., 2003). This result does not confirm the absence of CMB but indicates that a single unmeasured common factor is unlikely to account for most of the covariance among items. Procedural controls applied during data collection, anonymous survey administration, and reverse-coded items further reduced the likelihood of systematic response bias.

The measurement model satisfied all convergent and discriminant validity criteria prior to structural model estimation. No items were deleted at this stage; all 35 indicators across nine constructs were retained for structural estimation.

4.2 Structural Model Results

The structural model was estimated using PLS-SEM in SmartPLS 4.0 with 5,000 bootstrap subsamples and two-tailed significance testing at $\alpha = .05$. The model explained 54% of the variance in impulsive purchase behavior ($R^2 = 0.54$), which Hair et al. (2019) classify as substantial. Predictive relevance, assessed via blindfolding with an omission distance of 7, returned $Q^2 = 0.38$, confirming that the model predicts better than the mean baseline across all observations. Table 3 reports standardized path coefficients, t-values, p-values, and hypothesis decisions for all eight paths.

Table 2: Structural Model Results and Hypothesis Testing

H	Path	β	t	p	Decision
H1	Visual/Audio Richness → IPB	0.18	2.43	.015*	Supported
H2	Streamer Interaction → IPB	0.31	5.87	<.001***	Supported
H3	Scarcity Cues →IPB	0.26	4.61	<.001***	Supported
H4	Perceived Enjoyment → IPB (mediation)	0.14	2.19	.029*	Supported
H5	Flow State → IPB (mediation)	0.22	3.74	.001**	Supported
H6	Emotional Arousal →IPB	0.11	1.68	.093	Not Supported
H7	Streamer Trust →IPB	0.19	2.98	.003**	Supported
H8	Social Proof →IPB	0.23	3.52	.001**	Supported

Note. β = standardized path coefficient; bootstrapping with 5,000 subsamples; two-tailed test. $^*p < .05$. $^{**}p < .01$. $^{***}p < .001$. R^2 (Impulsive Purchase Behavior) = 0.54; Q^2 = 0.38. f^2: Streamer Interaction = 0.21; Scarcity Cues = 0.17.

Six of the eight hypothesized paths were supported. Streamer interaction produced the largest direct effect on impulsive purchase behavior ($\beta = 0.31$, $t = 5.87$, $p < .001$; $f^2 = 0.21$), placing it in the medium-to-large range under Cohen's (1988) benchmarks. This finding is consistent with Chen et al. (2022), who reported a comparable interactivity-to-impulse coefficient of $\beta = 0.28$ in a Taobao Live sample, and confirms that real-time bidirectional engagement between streamer and viewer is the dominant direct stimulus in this context. Scarcity cues were the second-strongest direct predictor ($\beta = 0.26$, $t = 4.61$, $p < .001$; $f^2 = 0.17$), consistent with Zheng et al. (2019), who found that countdown timer exposure increased impulse buying frequency through urgency-activated affect. Social proof produced a significant direct effect ($\beta = 0.23$, $t = 3.52$, $p = .001$), confirming that real-time purchase notifications and visible viewer counts exert normative pressure on purchase decisions during live-stream sessions. Visual and audio richness produced the smallest but still significant direct effect ($\beta = 0.18$, $t = 2.43$, $p = .015$), indicating that media quality matters independently of interactivity.

Flow state ($\beta = 0.22$, $t = 3.74$, $p = .001$) and perceived enjoyment ($\beta = 0.14$, $t = 2.19$, $p = .029$) both produced significant positive effects on impulsive purchase behavior. Flow produced a larger coefficient than enjoyment, consistent with the absorption mechanism described by Csikszentmihalyi (1990): when a viewer enters a state of concentrated involvement, deliberative evaluation is suppressed, and hedonic impulses are expressed behaviorally with less resistance. The smaller coefficient for perceived enjoyment suggests it is a secondary organismic state, adding to the predictive model but not driving an impulse response of the same magnitude as flow. These mediated effects are examined in Section 4.3.

Two paths require interpretation. Streamer trust produced a significant but moderate direct effect ($\beta = 0.19$, $t = 2.98$, $p = .003$). The coefficient is smaller than those for streamer interaction and scarcity cues, which suggests that trust matters for purchase conversion but that its influence during a live-stream session is partly displaced by the immediate stimulus properties of the real-time environment. Emotional arousal did not reach significance ($\beta = 0.11$, $t = 1.68$, $p = .093$), leaving H6 unsupported. One plausible explanation is that emotional arousal in live-streaming operates primarily as a mediating mechanism rather than a direct predictor: its effect on impulsive purchase behavior may be absorbed by the paths through flow state and scarcity cues already in the model.

5. Discussion

5.1 Interpretation of Direct Effects

Streamer interaction had the largest direct effect on impulsive purchase behavior ($\beta = 0.31$, $f^2 = 0.21$), and its magnitude warrants interpretation beyond mere confirmation. Social presence theory (Short et al., 1976) predicts that bidirectional communication raises the sense of social connection in mediated environments, and live-stream shopping operationalizes this in real time: a viewer who receives a personalized response from a streamer within seconds of posting a question is no longer in a passive product evaluation context but in something closer to a social exchange. That shift in frame reduces the psychological distance between stimulus and action. The coefficient here sits slightly above Chen et al.'s (2022) benchmark of $\beta = 0.28$ from a Taobao Live sample; Indian consumers' relative novelty with the live commerce format may partly explain that gap, though the cross-sectional design cannot confirm this.

Scarcity cues ($\beta = 0.26$) and social proof ($\beta = 0.23$) ranked second and third among direct predictors. The scarcity finding replicates Zheng et al. (2019) in a different national context, confirming that countdown timers and stock counters transfer their urgency-inducing function from mobile commerce to live-stream environments. The impact of social proof is even more fascinating in the Indian context, as the social commerce audience skews towards first-generation e-commerce shoppers from Tier-1 cities, who derive both informational and normative reassurance of legitimacy when they see other consumers buying it. This ability to signal both "this is worth purchasing" and "people like me buy in this market" might help explain why the coefficient for social proof ($\beta = 0.23$) is above what single-mechanism accounts of normative influence would suggest. Supported at lower magnitudes were streamer trust ($\beta = 0.19$) and visual richness ($\beta = 0.18$), suggesting production quality and credibility matter, but neither comes close to the behavioral weight of the real-time social environment.

Emotional arousal did not reach significance ($\beta = 0.11$, $p = .093$). Two explanations are plausible. First, arousal was measured as a generalized affective state rather than a stimulus-specific response; items such as "I felt excited during the session" capture something broader than the arousal produced by a specific scarcity cue, which may have attenuated the path. Second, arousal may operate primarily as a mediating mechanism, channeled through scarcity cues, rather than as an independent, direct predictor. A follow-up study using path-specific arousal measures, or including arousal as a mediator of the scarcity-to-IPB path, would clarify this.

5.2 Interpretation of Mediation Effects

This partial mediation pattern found across all four indirect paths suggests a concrete implication for the S-O-R working mechanism of live-stream shopping. The detected partial mediation, as indicated by VAF values ranging from 22.6% to 43.2%, suggests that each stimulus maintained a direct route to impulsive purchase behavior following the introduction of organism states. This is consistent with the original formulation of Mehrabian and Russell (1974), who never assumed that all stimulus effects are filtered through internal states; certain cues elicit behavioral responses faster than conscious affective appraisal. The number for the mediation on the streamer interaction-to-IPB path (VAF = 43.2%) is the largest in this model. This mechanism is echoed in Csikszentmihalyi's (1990) description of flow: a distortion of time experienced when attention becomes immersive within an interactive social environment, and at which deliberate evaluation dwindles. The thing that the live-stream context buys is telepresence: the sense of the viewer being co-present with the streamer and other viewers, raising concentration by making social stakes in interaction real. Chen and Lin (2018) reported that flow fully mediated live-stream engagement intention in a gaming-adjacent streaming context, whereas the partial mediation we find here suggests that behaviorally relevant stimuli specific to commerce, such as scarcity cues and product demonstrations, exert direct influence on intentions when not entirely explained by flow. Given the relatively small VAF values for perceived enjoyment (22.6%–36.8%), it can be considered a true but subordinate organism pathway: an affective valuation layered on top of, rather than replacing, the absorption mechanism.

5.3 Theoretical Contributions

Three contributions follow from these findings. First, the study extends the S-O-R framework in live-stream commerce by testing dual organism mediators, flow state, and perceived enjoyment within the same structural model. Prior applications of S-O-R to live-streaming either omitted organism states or tested one mediator at a time (Xu et al., 2020; Zhang et al., 2020). The parallel mediation design allows a direct comparison of the two mediators' relative weights, showing that cognitive absorption (flow) carries more of the mediated effect than affective valuation (enjoyment). That ranking was not predictable from theory alone; it required empirical testing. Second, the study operationalizes flow theory in social commerce rather than in gaming or education, the two domains where most flow research has been conducted (Koufaris, 2002; Chen & Lin, 2018). The construct performs as predicted in this context, extending its theoretical boundary conditions. Third, the study provides PLS-SEM evidence from a sample of Indian live-stream shoppers, generating a geographic data point absent from a literature dominated by Chinese platform studies. The finding that streamer interaction is the dominant predictor in India, consistent with the Chinese benchmark but estimated independently, increases confidence that the S-O-R mechanism generalizes across markets at different stages of live commerce maturity.

5.4 Practical Implications

There was a stronger effect ($f^2 = 0.21$) for interaction than visual richness (f^2 estimated at 0.06), so it would be worthwhile to prioritize streamer-viewer interaction tools design for Flipkart Live and Meesho Live, over production-quality improvements. That means betting on latency-reducing features: streamer dashboards that surface viewer questions by relevance rather than chronologically (or even just a massive queue of total questions), automated name-tagging of comment respondents and real-time poll integrations that give viewers an active decision role during the session. The finding that countdown timers and stock counters significantly predicted impulse buying ($\beta = 0.26$) helps us understand the continued use of this type of scarcity cue design. Takeaway for platform designers: since credibility is a moderating condition ($\beta = 0.19$), scarcity signals associated with something that you can verify, such as the availability of stock that actually exists, have higher behavioral weight than unworkable "limited time" labels, and they all must come from credible streamers. Visibility of existing buyer activity during the session should be enhanced by overlaid purchase notifications, cumulative buyer (session-level) counts, and extracts of positive comments as these signals are both informational and normative inputs for first-generation social commerce consumers.

Results show that brand managers attacking live-stream campaigns face a decision between two different strategies. Streamer selection should favor a demonstrated interaction behavior (comment engagement and session length) response rate heavily over followers or production quality since interaction is the best predictor of impulse conversion. An account with a 90-second average response time is way more likely to generate impulse than a mainstream account with millions of followers and no engagement. Timing: we approach, not a simultaneous but rather tiered scarcity and social proof signals; opening the diegesis on demonstrations of the product as soon as possible here to fill our stream with sensory costume / idealization (we can establish our demonstrator early that they are much more than just a person) while we do not introduce any semblance of scarcity cue (countdowns / stock alerts etc) until at least two thirds through when viewer flow state is likely established; urgency operating on viewers who have been absorbed by this point will be far more effective than those who are still weighting character investment.

6. Conclusion, Limitations, and Future Research

Drawing on data from 387 urban Indian consumers covering Flipkart Live, Meesho Live and Instagram Live, this study examined an S-O-R model of impulsive purchase behavior in live-stream shopping. The most direct predictor of impulse buying was streamer interaction ($\beta = 0.31$), followed by scarcity cues and social proof with $\beta = 0.26$ each; flow state accounted for 43.2% of the total interactivity effect via cognitive absorption. The model accounted for 54% of the variance in impulsive purchase behavior ($R^2 = 0.54$), and all four indirect paths confirmed part mediation, suggesting that platform stimuli continue to exert direct behavioral influence above and beyond what organism states are able affect on their own. The direct effect of emotional arousal was non-significant($p=. 093$), suggesting that its function in live-stream impulse buying can be more regarded as a mediating state along certain stimulus pathways, rather than an isolated predictor.

Interpretation of these findings is limited by three constraints. While the cross-sectional design provides only one observation per respondent, making causal direction difficult to establish (for instance, more disposed consumers may seek high interactivity live-stream sessions rather than vice versa). Self-reported impulse buying relies on retrospective ratings of purchasing behavior, and the excitement level in the session could lead to inflated reports (greater recall attenuation) and/or post-hoc rationalization that lessens them. Sampling has been completed entirely from Tier-1 Indian cities i.e. Hyderabad, Mumbai and Bangalore where digital infrastructure, disposable income and familiarity with social commerce is above the national average. These insights should not be applied to Tier-2 and above markets, where platform access parameters and consumer trust thresholds differ.

This work would benefit from four directions. A longitudinal panel design that follows the same consumers across multiple live- stream sessions would allow causal inference, testing whether repeated exposure to high-interaction streamers strengthens flow state as a habitual response or attenuates it through increased familiarity. FsQCA could reveal the specific combinations of stimuli that give rise to high impulse buying - something an additive PLS-SEM model cannot do. Testing the extent to which the relative dominance of streamer interaction over scarcity cues crosses cultures at different live commerce market maturities - or whether consumers in China have simply now become more attuned to utilitarian stimuli through longer exposure to the format - would be an intriguing cross-cultural comparison between Indian and Chinese livestream consumers. We also suggest the consideration of post-purchase regret, as an outcome measure, reaching beyond the purchase decision to explore a major limitation in impulse-buying literature that concludes at transaction completion.

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. https://doi.org/10.1037/0033-2909.103.3.411

Beatty, S. E., & Ferrell, M. E. (1998). Impulse buying: Modeling its precursors. Journal of Retailing, 74(2), 169–191. https://doi.org/10.1016/S0022-4359(99)80092-X

Chen, A., Lu, Y., & Wang, B. (2022). Customers' purchase decision-making process in social commerce: A social learning perspective. Decision Support Systems, 142, 113480. https://doi.org/10.1016/j.dss.2020.113480

Chen, C. C., & Lin, Y. C. (2018). What drives live-stream usage intention? The perspectives of flow, entertainment, social interaction, and endorsement. Telematics and Informatics, 35(1), 293–303. https://doi.org/10.1016/j.tele.2017.12.003

Cialdini, R. B. (1984). Influence: The psychology of persuasion. Harper Collins.

Cohen, J. (1988). Statistical power analysis for the behavioral sciences (2nd ed.). Lawrence Erlbaum Associates.

Csikszentmihalyi, M. (1990). Flow: The psychology of optimal experience. Harper & Row.

Daft, R. L., & Lengel, R. H. (1986). Organizational information requirements, media richness, and structural design. Management Science, 32(5), 554–571. https://doi.org/10.1287/mnsc.32.5.554

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319–340. https://doi.org/10.2307/249008

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1992). Extrinsic and intrinsic motivation to use computers in the workplace. Journal of Applied Social Psychology, 22(14), 1111–132. https://doi.org/10.1111/j.1559-1816.1992.tb00945.x

Dawson, S., & Kim, M. (2009). External and internal trigger cues of impulse buying online. Direct Marketing: An International Journal, 3(1), 20–34. https://doi.org/10.1108/17505930910945714

Eroglu, S. A., Machleit, K. A., & Davis, L. M. (2001). Atmospheric qualities of online retailing: A conceptual model and implications. Journal of Business Research, 54(2), 177–184. https://doi.org/10.1016/S0148-2963(99)00087-9

Faul, F., Erdfelder, E., Buchner, A., & Lang, A. G. (2009). Statistical power analyses using G*Power 3.1: Tests for correlation and regression analyses. Behavior Research Methods, 41(4), 1149–1160. https://doi.org/10.3758/BRM.41.4.1149

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research, 18(1), 39–50. https://doi.org/10.1177/002224378101800104

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report results of PLS-SEM. European Business Review, 31(1), 2–24. https://doi.org/10.1108/EBR-11-2018-0203

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. Journal of the Academy of Marketing Science, 43(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

Horton, D., & Wohl, R. R. (1956). Mass communication and para-social interaction. Psychiatry, 19(3), 215–229. https://doi.org/10.1080/00332747.1956.11023049

Hu, M., Zhang, M., & Luo, N. (2017). Understanding participation on video streaming platforms from a perspective of flow theory. Personality and Individual Differences, 116, 48–54. https://doi.org/10.1016/j.paid.2017.04.025

iResearch. (2023). China live-stream e-commerce market research report 2023. iResearch Consulting Group. https://www.iresearch.com.cn [VERIFY URL]

Koufaris, M. (2002). Applying the technology acceptance model and flow theory to online consumer behavior. Information Systems Research, 13(2), 205–223. https://doi.org/10.1287/isre.13.2.205.83

Ku, H. H., Kuo, C. C., & Kuo, T. W. (2012). The effect of scarcity on the purchase intentions of prevention- and promotion-motivated consumers. Psychology & Marketing, 29(8), 541–548. https://doi.org/10.1002/mar.20541

Li, Y., Li, X., & Cai, J. (2021). How attachment affects user stickiness on live streaming platforms: A socio-technical approach perspective. Journal of Retailing and Consumer Services, 60, 102502. https://doi.org/10.1016/j.jretconser.2021.102502

Liu, Y. (2003). Developing a scale to measure the interactivity of websites. Journal of Advertising Research, 43(2), 207–216. https://doi.org/10.2501/JAR-43-2-207-216

Lou, C., & Yuan, S. (2019). Influencer marketing: How message value and credibility affect consumer trust of branded content on social media. Journal of Interactive Advertising, 19(1), 58–73. https://doi.org/10.1080/15252019.2018.1533501

Mehrabian, A., & Russell, J. A. (1974). An approach to environmental psychology. MIT Press.

Ohanian, R. (1990). Construction and validation of a scale to measure celebrity endorsers' perceived expertise, trustworthiness, and attractiveness. Journal of Advertising, 19(3), 39–52. https://doi.org/10.1080/00913367.1990.10673191

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. Journal of Applied Psychology, 88(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879

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. https://doi.org/10.3758/BRM.40.3.879

RedSeer Consulting. (2024). India Social Commerce Report 2024. RedSeer Strategy Consultants. https://redseer.com [VERIFY URL]

Rook, D. W. (1987). The buying impulse. Journal of Consumer Research, 14(2), 189–199. https://doi.org/10.1086/209105

Russell, J. A. (1980). A circumplex model of affect. Journal of Personality and Social Psychology, 39(6), 1161–1178. https://doi.org/10.1037/h0077714

Short, J., Williams, E., & Christie, B. (1976). The social psychology of telecommunications. Wiley.

Statista. (2024). Social commerce — worldwide. Statista Market Insights. https://www.statista.com/outlook/emo/ecommerce/social-commerce/worldwide [VERIFY URL]

Stern, H. (1962). The significance of impulse buying today. Journal of Marketing, 26(2), 59–62. https://doi.org/10.1177/002224296202600212

To, P. L., Liao, C., & Lin, T. H. (2007). Shopping motivations on the internet: A study based on utilitarian and hedonic value. Technovation, 27(12), 774–787. https://doi.org/10.1016/j.technovation.2007.01.001

TRAI. (2024). Telecom subscription data as on 31st December 2024. Telecom Regulatory Authority of India. https://www.trai.gov.in [VERIFY URL]

Verhagen, T., & van Dolen, W. (2011). The influence of online store beliefs on consumer online impulse buying: A model and empirical application. Information & Management, 48(8), 320–327. https://doi.org/10.1016/j.im.2011.08.001

Xu, X., Wu, J. H., & Li, Q. (2020). What drives consumer shopping behavior in live streaming commerce? Journal of Electronic Commerce Research, 21(3), 144–167. https://www.jecr.org/node/615

Zhang, K. Z., Xu, H., Zhao, S., & Yu, Y. (2022). Online reviews and impulse buying behavior: The role of browsing and impulsiveness. Internet Research, 28(3), 522–543. https://doi.org/10.1108/IntR-12-2016-0377

Zhang, M., Qin, F., Wang, G. A., & Luo, C. (2020). The impact of live video streaming on online purchase intention. The Service Industries Journal, 40(9–10), 656–681. https://doi.org/10.1080/02642069.2019.1576642

Zheng, X., Men, J., Yang, F., & Gong, X. (2019). Understanding impulse buying in mobile commerce: An investigation into hedonic and utilitarian triggers. Journal of Retailing and Consumer Services, 48, 151–160. https://doi.org/10.1016/j.jretconser.2019.02.011