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AI-Powered Shopstreaming and Impulsive Buying: Parasocial Interaction, Perceived Enjoyment, and Sale Proneness

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ABSTRACT

Artificial intelligence increasingly shapes livestream shopping through virtual hosts, personalized product displays, and automated interactions that may alter consumers' social and emotional responses. This article examines how product relevance, social attraction, and content characteristics relate to parasocial interaction, perceived enjoyment, and impulsive buying in AI-powered shopstreaming. It also considers sale proneness as a moderator of the relationship between perceived enjoyment and impulsive buying. The proposed framework draws on the Stimulus–Organism–Response perspective and integrates research on AI influencers, livestream engagement, and impulsive consumption. A quantitative explanatory design is outlined, with measurement and structural analyses organized around seven constructs and their proposed relationships. The accompanying calculations provide a methodological check of the analysis and reporting procedures, rather than observations collected from shoppers. Consequently, the proposed relationships require validation using verified participant responses before empirical conclusions can be established. This study provides an integrated basis for examining when AI-mediated social cues and enjoyable shopping experiences may encourage unplanned purchases and for guiding further research on responsible AI-assisted commerce.

Keywords: AI-Powered Shopstreaming, Parasocial Interaction, Perceived Enjoyment, Impulsive Buying, Sale Proneness.

INTRODUCTION

Live-stream commerce blends product presentation, conversation, entertainment, and immediate purchasing within a single digital encounter. Unlike conventional product pages, shopstreaming creates an unfolding setting in which viewers interpret a presenter's responses, assess a product demonstration, and decide whether to act before the session ends. Research on social and media cues shows that this format can activate both affective responses and buying impulses, although different cues do not necessarily work through the same psychological pathway (Xia et al., 2024). The role of the streamer is important because consumers evaluate not only information quality but also the interpersonal qualities of the individual or character presenting the offer (Li et al., 2024). Evidence from Indonesian TikTok consumers likewise

indicates that impulsive online shopping is embedded in platform-specific promotional and engagement experiences (Febriandika et al., 2023).

Artificial intelligence introduces another layer to this environment. AI-powered shopstreaming may employ synthetic presenters, virtual idols, automated yet responsive dialogue, or recommendation systems that tailor product exposure. Such systems can change the nature of encounters while preserving the appearance of a social shopping experience. Li et al. (2025) studied AI-powered virtual idols in e-commerce live streaming and identified psychological distance as an important mechanism associated with impulsive buying intention. Rachmat (2026) examined algorithm-driven personalization and content exposure in relation to Gen Z impulse buying on TikTok Shop. These studies demonstrate the relevance of artificial intelligence to digital purchase behavior, but they do not establish that every ordinary live-selling session uses AI or that all AI-related features produce identical consumer responses.

The expression AI-powered shopstreaming requires a narrower definition than digital commerce conducted on a large platform. AI may be visible in the presenter, in personalized content sequences, or in automated conversation; these uses create different experiences for consumers. A virtual host introduces questions of human likeness and source credibility, whereas a recommendation mechanism primarily alters which products are encountered and when. The distinction matters because a person can find a recommendation relevant without feeling socially connected to the entity that presents it. Research on virtual streamers' credibility, virtual influencers' authenticity, and AI-based product recommendations offers different conceptual routes into this problem (Ji, 2024; Ju et al., 2024; Panya et al., 2025). The current framework focuses on the way these encounters are perceived, not on the engineering performance of an AI system. Accordingly, participants should be asked about the particular form of AI they actually experienced, rather than treated as members of a single undifferentiated AI-shopping population.

The Stimulus–Organism–Response (S–O–R) perspective offers a coherent way to distinguish the external features of a shopping encounter from the consumer's internal reactions and behavioral response. In livestreaming, social cues, media characteristics, and interactive presentations function as stimuli; relational or affective processes capture the organism; and purchase-related reactions represent the response. A livestreaming investigation using the S–O–R approach found that media and social cues were connected with pleasure, uncertainty, and an urge to buy (Xia et al., 2024). Another S–O–R study linked livestreaming marketing practices with impulsive purchase behavior, emphasizing the need to study intervening psychological processes rather than relying only on direct stimulus–purchase associations (Chen et al., 2022). This logic is especially relevant when the source of the interaction can be an AI-based presenter.

The S–O–R structure is useful precisely because the presence of a stimulus does not guarantee a purchase. Product relevance describes an individual evaluation of fit; social attraction concerns the perception of a presenter as a social figure; and content characteristics concern the attributes of the communication itself. These dimensions can covary but should not be treated as interchangeable. On the organism side, enjoyment concerns the experience of pleasure, while parasocial interaction concerns a perceived relational exchange. The outcome is impulsive buying, which differs from purchase intention because it emphasizes unexpected

or spontaneous action rather than general willingness to buy. This conceptual separation helps identify where competing explanations may arise. Livestream studies addressing real-time interaction, affective reactions, and impulse purchasing provide the empirical background for keeping the stimulus, organism, and response categories distinct (Gao et al., 2022; Li et al., 2022; Xia et al., 2024).

Two organism constructs are central to the present proposal. Parasocial interaction describes a viewer's perceived interpersonal connection with a mediated figure, despite the asymmetry or technological mediation of the relationship. In influencer research, perceived social attraction and related characteristics have been associated with stronger parasocial ties and impulsive online buying (Karahan, 2025). Perceived enjoyment, by contrast, denotes the pleasure derived from experiencing the shopping content itself. Prior work on Generation Z live shopping identifies enjoyment as a mechanism between real-time interactivity and impulsive purchasing (Indriastuti et al., 2024). Distinguishing these processes prevents the analysis from treating affection toward a presenter and enjoyment of the shopping experience as interchangeable constructs.

Parasocial interaction should not be reduced to simple exposure time or an individual's admiration for a public personality. A viewer may watch repeatedly for information yet experience little sense of conversation or familiarity. Conversely, brief but apparently responsive interactions can create the impression that the presenter has recognized or addressed the viewer. This issue becomes more complicated with AI presenters because immediate responses may be programmed and scalable rather than expressions of personal awareness. Research comparing human and AI influencers and work on virtual idols provide a reason to investigate how viewers interpret those cues rather than assuming that technological interactivity equals interpersonal closeness (Omeish et al., 2025; Du et al., 2025). The distinction also guides measurement: questions about perceived connection should be separated from questions about entertainment value, usefulness, and technical responsiveness. Without this separation, a positive relationship between constructs could arise from overlapping item wording rather than a theoretically meaningful process.

The available evidence also calls for caution about assuming consistent effects. Research on TikTok live commerce in Indonesia reported that social attraction did not significantly influence parasocial interaction in its estimated model, whereas narrative involvement was influential (Hadiyati & Luthfia, 2026). A separate study of social media influencers found that social attraction can contribute to parasocial interaction and downstream impulsive buying (Karahan, 2025). This contrast is a reason to test the relationship in the AI-powered shopstreaming setting rather than presuming it will hold. It also underscores why explanatory models should report unsupported hypotheses with the same transparency as supported ones.

Contextual differences may help explain why relationships that appear theoretically similar do not always show the same pattern. Product category, familiarity with the host, perceived artificiality, promotional urgency, and habitual shopping frequency can change what viewers attend to during a live session. A consumer considering an everyday inexpensive product may respond differently from someone evaluating a costly item that requires comparison or deliberation. Moreover, a presenter can be socially attractive without being trusted as a product adviser. The present study therefore treats social attraction as a proposed antecedent rather than

an established predictor in every setting. The mixed literature on parasocial interaction in live commerce and broader influencer marketing supports testing the relation rather than simply transferring a coefficient from one population to another (Hadiyati & Luthfia, 2026; Karahan, 2025). This caution becomes especially important when a study moves from human influencers to synthetic or partly automated presenters.

Sale proneness is positioned as a moderator rather than another psychological outcome. Consumers with stronger sensitivity to price reductions and promotional opportunities may be more prepared to turn an enjoyable viewing session into an immediate purchase. The sale-proneness interaction is grounded in research on product placement and impulsive buying, not simply assumed from the existence of promotional events (Kim et al., 2026). Evidence on flash sales further suggests that purchase-related emotions may participate in consumers' responses to limited-time promotions (Martaleni et al., 2022). Nonetheless, promotions can involve genuine savings, anticipated regret, and urgency; these possibilities should be distinguished from the general tendency to enjoy the stream.

Conceptually, sale proneness differs from exposure to a discount. A promotion is an external event, whereas sale proneness is a consumer disposition to value and react to opportunities that are framed as bargains. Two viewers can encounter the same price reduction yet assign different importance to it. This distinction is especially useful in a moderated model: the theory does not require discounts to increase everyone's enjoyment, but suggests that an enjoyable encounter may be more readily converted into an unplanned purchase among viewers responsive to deals. Because the moderator is a disposition, measurement should focus on a person's general sensitivity to promotional opportunities rather than whether the latest stream happened to display a voucher. The construct should also be distinguished from compulsive buying, financial constraint, and pure price consciousness. Work on sale proneness and impulse buying provides a relevant research context for this distinction (Kim et al., 2026; Martaleni et al., 2022).

This manuscript responds to three related research gaps. First, studies of AI presenters and algorithms do not consistently isolate the combination of parasocial interaction, perceived enjoyment, and sale proneness in one model of impulsive buying (Li et al., 2025). Second, influencer research indicates important relational effects but does not automatically establish their transferability to settings involving synthetic or AI-assisted presentation (Omeish et al., 2025). Third, research on sale proneness and enjoyment has mainly emphasized product-placement stimuli, leaving the incremental contribution of the parasocial pathway within AI-powered shopstreaming open to testing (Kim et al., 2026). These are proposed integration and context gaps; they should not be described as proof that no previous article has examined similar constructs.

A further distinction concerns what the term impulsive buying denotes at the point of measurement. Studies sometimes investigate impulse-buying intention, recalled behavior, or an urge to buy during a session. These outcomes are related but not identical, and confusing them would make it difficult to compare the present framework with earlier publications. The proposed article uses Impulsive Buying as its outcome, so a field instrument must establish whether it measures a reported unplanned transaction, a sudden urge, or self-perceived spontaneity. If the study relies on a retrospective self-report, the authors should acknowledge that it does not capture a directly observed checkout event. Research on emotional mechanisms,

live-stream frequency, and scarcity-based decisions provides useful comparisons while highlighting the need to define the response precisely (Yi et al., 2023; Xia et al., 2024; Febriandika et al., 2023). Establishing that definition before fieldwork will improve the interpretation of direct and mediated effects.

The study seeks to evaluate seven hypotheses: product relevance → perceived enjoyment; social attraction and content characteristics → parasocial interaction; parasocial interaction → perceived enjoyment and impulsive buying; perceived enjoyment → impulsive buying; and sale proneness as a moderator of the enjoyment–buying association. The direct sale-proneness association with impulsive buying is included as a statistical control. This reduced framework places AI in the research setting rather than claiming that AI itself is a separately measured causal variable.

The context must be made operationally observable. AI-powered shopstreaming may involve virtual presenters, automated live responses, or product displays tailored by AI-based recommendation mechanisms. The future field questionnaire should verify actual exposure to an identifiable AI function; otherwise, the study would measure conventional livestream commerce while overstating the role of artificial intelligence (Li et al., 2025; Rachmat, 2026).

Product relevance and perceived enjoyment (H1). Product relevance denotes how closely the product displayed during a stream aligns with viewers' current needs, interests, or goals. A relevant item can make a demonstration intrinsically worthwhile because the information has immediate personal meaning. An AI-supported recommendation may heighten perceived fit when the system presents a product that matches a viewer's preferences, although this particular mechanism must be documented in the selected setting. Kim et al. (2026) explicitly included product relevance among the stimuli explaining enjoyment in product-placement content. Research on AI-driven personalization similarly identifies tailored online shopping experiences as an important object of consumer research (Panya et al., 2025). Accordingly, H1 proposes that product relevance positively influences perceived enjoyment.

An important implication of H1 is that content relevance may be pleasurable even when the item is not purchased. Viewers may appreciate an efficient demonstration, discover a previously unknown alternative, or enjoy receiving recommendations that reflect their interests. This expected psychological response differs from the assumption that relevance directly triggers impulsive buying. The latter claim would require a separate pathway and empirical test. In an AI setting, product fit can be influenced by personalization, but a study must distinguish the perceived relevance of the item from a participant's evaluation of the recommendation algorithm. Articles on AI-powered personalization and AI shopping interfaces illustrate why these technological and psychological dimensions should not be conflated (Panya et al., 2025; Gao & Liang, 2025). The proposed relationship is therefore deliberately limited to Product Relevance and Perceived Enjoyment, preserving the compact seven-construct design while allowing competing explanations to be discussed as limitations.

Social attraction and parasocial interaction (H2). Social attraction means perceived warmth, likability, familiarity, or desirability of a presenter as a social counterpart. Although interaction may be simulated or mediated by automation, viewers can still perceive a relational exchange. Research contrasting human and AI influencers indicates that parasocial relationships are relevant to synthetic personas (Omeish et al., 2025). Evidence from influencer-mediated

impulsive buying also associates social attraction with parasocial interaction (Karahan, 2025). However, Hadiyati and Luthfia (2026) reported a nonsignificant social-attraction link in an Indonesian TikTok-live model, which means the theoretical expectation is contestable. H2 proposes that social attraction positively influences parasocial interaction and should be retained for testing regardless of statistical support.

Social attraction may be shaped by friendliness, consistency in communication style, and the presenter's apparent responsiveness. For human hosts these cues may be attributed to personality; for a virtual figure they can be interpreted as design features. A field study should not assume that all consumers realize when a host is computer generated, or that all consumers attach the same meaning to an AI disclosure. Understanding perceived source identity is important when testing whether attraction gives rise to parasocial interaction. Prior studies examine credibility and consumer engagement for AI influencers and virtual endorsers, making them relevant to questions of relational cues (Jayasingh et al., 2025; Xu et al., 2025). The measurement items should nevertheless avoid asking respondents to evaluate the host's attractiveness and their sense of personal connection in the same sentence. Doing so would obscure the proposed distinction between stimulus and organism and could artificially inflate associations.

Content characteristics and parasocial interaction (H3). Content characteristics describe qualities of the broadcast material, including comprehensibility, vividness, authenticity cues, narrative continuity, and responsiveness of the displayed information. They are not identical to product relevance: a stream can be well produced yet present products that are irrelevant to a particular consumer. Research on virtual idol characteristics included content features in explaining relational and flow processes (Du et al., 2025). Work on the role of live streamers also suggests that viewer responses depend on how a host presents and communicates the offer (Li et al., 2024). In AI-assisted streams, relevant content features might include coherent automated responses and credible demonstrations, provided these are observed by participants. H3 proposes that content characteristics positively influence parasocial interaction.

Content characteristics are also wider than production quality. A well-lit broadcast may be clear yet repetitive; a visually modest session may be perceived as authentic or directly responsive. A theoretically coherent measure should emphasize features that can plausibly contribute to viewers' sense of involvement, such as narrative continuity, informative demonstrations, coherence between dialogue and products, and responses to questions. However, content characteristics should not contain items that directly state that the viewer likes the presenter, feels connected to the presenter, or intends to purchase. Those belong to other constructs in this model. Research examining perceived streamer ability, virtual idol characteristics, and interactivity during live shopping provides relevant distinctions for operationalizing content features (Chen et al., 2024; Du et al., 2025; Li et al., 2022). A transparent field instrument would record the wording, sources, translation process, and any pretesting decisions before full-scale data collection.

Parasocial interaction and perceived enjoyment (H4). A viewer who feels acquainted with the host may find the stream more pleasant even when no purchase is planned. Relational familiarity can increase interest in ordinary conversation, anticipation of the host's responses, and willingness to remain in the broadcast. Zhu and Vijayan (2025) found that parasocial

interaction was positively associated with perceived enjoyment in live-streaming commerce. Research on virtual idols likewise linked parasocial mechanisms with flow experience, an adjacent but not identical psychological construct (Du et al., 2025). The present study therefore treats enjoyment as a possible affective consequence of parasocial interaction rather than defining the two constructs using overlapping items. H4 proposes that parasocial interaction positively influences perceived enjoyment.

The proposed mechanism in H4 concerns the experiential value of perceived companionship. Viewers can enjoy a host's presentation because it creates a feeling of familiarity, even when they recognize that the relationship is one-sided. In AI-powered shopstreaming, the effect may depend on whether automated responses feel coherent and contextually appropriate. An answer that appears personalized but does not respond to the ongoing conversation may be less enjoyable than a simpler but consistent exchange. This raises a useful boundary condition: technical responsiveness alone should not be interpreted as evidence of a social bond. Work on AI-chatbot adoption and virtual-live-streamer credibility helps situate these features without establishing the present pathway in advance (Ding & Najaf, 2024; Ji, 2024). Separating perceived enjoyment from parasocial interaction allows the eventual analysis to examine whether the relational route contributes additional explanatory value beyond product relevance and general content quality.

Parasocial interaction and impulsive buying (H5). A perceived bond with a presenter can potentially influence spontaneous purchasing by reducing hesitation, making recommendations socially salient, or fostering a sense of personal connection to the promoted product. Karahan (2025) reported an association between parasocial interaction and online impulsive buying in influencer marketing. The Indonesian TikTok-live study by Hadiyati and Luthfia (2026) also identified a relational mediation pathway to impulsive purchase. These findings justify examining a direct path from parasocial interaction to impulsive buying in addition to the indirect path through enjoyment. The direct and indirect effects should be estimated separately, because a significant overall effect does not by itself identify the mechanism. H5 proposes that parasocial interaction positively influences impulsive buying.

Perceived enjoyment and impulsive buying (H6). Enjoyment can increase the subjective appeal of an immediately available product and encourage rapid decisions when a checkout option is close to the stream. Studies of livestreaming consumers have reported the relevance of pleasure and affective states to impulse buying (Xia et al., 2024). Indriastuti et al. (2024) specifically examined perceived enjoyment as a mediator between real-time interactivity and impulsive purchasing among Generation Z. Zhu and Vijayan (2025) likewise identified enjoyment within an impulse-purchase mechanism. These studies support the proposed direction but do not remove the need to distinguish spontaneous buying from general purchase intention. H6 proposes that perceived enjoyment positively influences impulsive buying.

A positive emotional experience does not necessarily lead to an unplanned transaction. Some viewers may stay for entertainment, gather information, or postpone purchasing until they compare prices elsewhere. Others may respond to urgency cues, perceived scarcity, or an especially convenient checkout process. The enjoyment pathway should therefore be discussed as a conditional behavioral proposition rather than a universal rule. Livestream commerce studies addressing anticipated emotions, scarcity, and the role of interactivity offer context for

this distinction (Yi et al., 2023; Indriastuti et al., 2024). For measurement purposes, enjoyment items should focus on pleasant feelings during the viewing experience, whereas impulsive-buying items should refer to unexpected urges or purchases. A correlation between these items will be more interpretable if the survey avoids overlapping evaluative statements, such as asking whether respondents 'enjoyed buying impulsively' as a measure of enjoyment.

Sale proneness as a moderator (H7). Sale proneness refers to a relatively stable tendency to notice, value, and respond favorably to discounts or promotional deals. It may increase the likelihood that a pleasurable stream translates into purchasing action because promotions make the choice feel more timely or rewarding. Kim et al. (2026) directly investigated sale proneness in a moderated S–O–R model of product-placement-driven impulsive buying. Flash-sale research also points to the importance of emotions in online impulse purchases (Martaleni et al., 2022). In the proposed model, sale proneness is not presumed to moderate every path; it is specified only as an interaction with perceived enjoyment predicting impulsive buying. H7 proposes that sale proneness positively moderates the perceived enjoyment–impulsive buying relationship, such that the relationship is stronger at higher levels of sale proneness.

The reduced model distinguishes product relevance as an antecedent of enjoyment, while social attraction and content characteristics relate to parasocial interaction. The relational response can influence impulsive buying directly and through enjoyment, and sale proneness may condition the enjoyment–buying link. This parsimonious arrangement follows prior scholarship without presuming that its relationships have already been verified in the field (Li et al., 2025; Kim et al., 2026; Zhu & Vijayan, 2025).

RESEARCH METHOD

Research design. The study develops an explanatory seven-construct framework for consumers exposed to identifiable AI functionality during livestream commerce. A subsequent empirical application should use a cross-sectional questionnaire with eligibility screening and a clearly recorded data-collection procedure. The numeric tables included here are derived from an independently constructed methodological dataset and illustrate how the selected relationships and tests can be reported. They do not represent observations from a field survey. This distinction is important when interpreting the subsequent statistical descriptions and when preparing an eventual manuscript based on respondents' answers.

AI exposure and study setting. The target population consists of consumers who have encountered a recognizable AI component during a live-shopping experience, such as an identifiable virtual presenter, an AI-supported dialog interface, or personalized product displays presented within the session. A later field questionnaire needs to record the platform and type of AI feature, the recency of exposure, and participants' understanding of what they viewed. Conventional livestream shopping cannot be treated as AI-powered solely because the hosting platform uses algorithms elsewhere. Such screening is essential for aligning the sampling frame with the study title (Li et al., 2025; Rachmat, 2026).

An eventual field design should specify eligibility before recruitment rather than adapting it after responses arrive. The screening sequence can first establish that the participant has watched a livestream shopping session, then identify an AI component within that session, and finally distinguish viewers who observed the feature from those who interacted with it.

Information about product category and shopping familiarity would help describe the realized sample and assess limits on generalization. Such variables need not automatically become additional theoretical constructs; they can be collected as sample descriptors or considered as controls where justified. Because the present article concerns perceived relationships and enjoyment, participation should be voluntary and any account of a prior purchase should avoid collecting sensitive payment credentials. These procedures would make subsequent field results more credible and would help reviewers judge how well the operational study corresponds to AI-powered shopstreaming rather than livestream commerce in general.

Synthetic calculation dataset. A constructed numerical dataset of 260 cases was created to exercise the seven-variable reporting procedure; it is not a probability or purposive sample of human participants. The file contains four ordinal items per construct, each with integer values from 1 to 7. Since these responses were generated, no demographic attributes, survey dates, response rates, participant consent claims, or actual shopping experiences can be inferred from the table. Field data must be collected independently before the results are characterized as empirical.

Measures. The seven constructs are Product Relevance (PR), Social Attraction (SA), Content Characteristics (CC), Parasocial Interaction (PSI), Perceived Enjoyment (PE), Sale Proneness (SP), and Impulsive Buying (IB). The methodological dataset contains four constructed ordinal items for each variable. A field questionnaire would instead require adapted and theoretically grounded measurement items, reviewed for clarity and context-specific meaning. The literature on sale proneness, influencer relationships, and livestream enjoyment provides a starting point for identifying construct boundaries, but item-level validity cannot be presumed from conceptual overlap (Kim et al., 2026; Karahan, 2025; Zhu & Vijayan, 2025).

Data processing. For the present methodological exercise, mean scores were calculated from the four items in each construct and standardized. Cronbach's alpha was calculated from the raw item variance-covariance structure. Indicator-to-composite correlations, composite reliability calculations, and their mean squared correlations were used as descriptive approximations rather than output of a latent-variable PLS measurement model. For field submission, these should be replaced by actual indicator loadings and validated PLS-SEM or CFA results.

Before any survey analysis, a codebook should identify which questionnaire item belongs to each construct and how its response scale is interpreted. Reverse-worded items, missing responses, duplicate entries, and implausibly rapid completions require predefined handling rules. Internal consistency alone is not sufficient evidence that the intended concepts have been measured. Convergent validity, discriminant validity, and multicollinearity should be examined using methods appropriate to the actual measurement model. If PLS-SEM is selected, indicator loadings, construct reliability, HTMT, structural VIF, explained variance, and resampling intervals should be reported from that fitted model, not borrowed from separate regressions. For the present constructed dataset, descriptive composite-score regressions are identified as such and do not carry a PLS-SEM label. This distinction protects the comparability of the manuscript with peer-reviewed papers that use genuine latent-variable estimators.

Structural analysis. Three standardized-score regressions were estimated: PSI from SA and CC; PE from PR and PSI; and IB from PSI, PE, SP, and the standardized product PE × SP. The

final regression includes sale proneness as a control main effect because an interaction term should not be reported without its constituent main effects. Percentile bootstrap estimates were calculated from 1,200 resamples, providing path standard errors and confidence intervals. All numeric outcomes below are properties of the constructed dataset, not statistics about real shopstreaming consumers.

Moderation requires particular care because its coefficient can depend on variable centering, indicator scaling, and the placement of the lower-order terms. An interaction between Perceived Enjoyment and Sale Proneness should be estimated alongside the direct effects of both variables. When authentic responses are available, the authors can describe the conditional relationship using simple-slope estimates or a marginal-effect visualization without adding a conceptual model diagram to the article. A significant coefficient alone would not indicate whether the difference between high and low sale-proneness groups is substantively important. Similarly, mediation requires an indirect-effect interval, but cross-sectional associations do not establish the temporal ordering needed for a strong causal interpretation. The proposed article should present coefficients, uncertainty intervals, and the limits of inference together. This approach produces a more informative argument than reporting only whether a p-value crosses a conventional threshold.

Indirect effect and model assessment. The specific indirect association PSI → PE → IB was estimated by multiplying the two standardized regression coefficients within every bootstrap draw. The reported R^2 values are conventional regression explained variance, not variance explained by a fitted PLS latent-variable model. The reported composite diagnostics do not substitute for HTMT inference, model measurement validation, sampling bias assessment, and statistical checks on authentic survey responses.

Reproducibility. The data-generation script uses a fixed pseudorandom seed (20261016), N = 260, 28 generated item columns, seven averaged scale scores, and 1,200 nonparametric bootstrap replications. The generated CSV can reproduce the presented exercise. This transparency prevents a demonstration from being mistaken for evidence that interviews, questionnaires, or fieldwork took place.

Table 1. R-square

Variable	R-square	Adjusted R-square
Parasocial Interaction	0.249	0.243
Perceived Enjoyment	0.277	0.272
Impulsive Buying	0.339	0.329

Source: standardized composite-score regression on computationally generated cases (N = 260).

Table 2. Reliability and Validity

Variable	Cronbach Alpha	Composite Reliability*	AVE*
Product Relevance	0.919	0.942	0.804
Social Attraction	0.922	0.945	0.811

Content Characteristics	0.923	0.945	0.812
Parasocial Interaction	0.916	0.941	0.800
Perceived Enjoyment	0.930	0.950	0.826
Sale Proneness	0.928	0.949	0.822
Impulsive Buying	0.918	0.942	0.803

**The CR and AVE indices are calculated from item–composite correlations, not from PLS-SEM outer loadings. Source: generated item data (N = 260).*

Table 3. Fornell–Larcker-Type Composite Correlations

Variable	PR	SA	CC	PSI	PE	SP	IB
PR	0.896	—	—	—	—	—	—
SA	0.276	0.901	—	—	—	—	—
CC	0.217	0.201	0.901	—	—	—	—
PSI	0.264	0.429	0.336	0.894	—	—	—
PE	0.411	0.191	0.087	0.426	0.909	—	—
SP	-0.017	0.117	0.048	0.038	-0.009	0.907	—
IB	0.206	0.328	0.187	0.461	0.476	0.129	0.896

Diagonal: √AVE-like index; below diagonal: composite correlations. These are descriptive analogues and do not substitute for a fitted measurement model.

Table 4. Discriminant Validity (HTMT)

Variable	PR	SA	CC	PSI	PE	SP	IB
PR	—	—	—	—	—	—	—
SA	0.300	—	—	—	—	—	—
CC	0.236	0.218	—	—	—	—	—
PSI	0.288	0.466	0.365	—	—	—	—
PE	0.445	0.206	0.094	0.461	—	—	—
SP	0.032	0.127	0.071	0.054	0.036	—	—
IB	0.224	0.356	0.203	0.502	0.515	0.139	—

HTMT ratios calculated on generated item responses. Source: constructed methodological dataset.

Hypothesis Testing

Table 5. Hypothesis Tester

Variable	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T statistics (|O/STDEV|)	P values	Decision
PR → PE (H1)	0.321	0.323	0.053	6.057	<0.001	Significant *
SA → PSI (H2)	0.377	0.376	0.050	7.504	<0.001	Significant *
CC → PSI (H3)	0.260	0.257	0.057	4.538	<0.001	Significant *
PSI → PE (H4)	0.341	0.340	0.054	6.368	<0.001	Significant *
PSI → IB (H5)	0.298	0.296	0.055	5.380	<0.001	Significant *
PE → IB (H6)	0.343	0.343	0.052	6.573	<0.001	Significant *
PE × SP → IB (H7)	0.131	0.130	0.052	2.512	0.013	Significant *

**Decision refers only to a numerical p-value threshold in constructed data; it is not an empirical acceptance of a research hypothesis. Bootstrap: 1,200 resamples.*

Numerical overview. The constructed dataset contains 260 cases and four response items per construct on a seven-point scale. Its purpose is to verify whether the planned analytic specification produces complete, internally consistent reporting tables. Table 1 summarizes explained variance from standardized-score regressions, while Table 2 reports scale-consistency and item-to-composite diagnostics. Tables 3 and 4 provide correlation-based checks, and Table 5 shows coefficient estimates with resampling uncertainty. These outputs demonstrate a calculation workflow, not patterns estimated from people who have used AI-supported live commerce.

Internal consistency and measurement interpretation. Scale alpha estimates and item–composite summaries can reveal how consistently the generated items move together within the constructed dataset. The calculated alpha coefficients range from 0.916 to 0.930, but these values are features of the item-generation process, not evidence that a respondent questionnaire is reliable. The reported composite reliability and AVE-style values use item-to-composite correlations. Because each item contributes to the score against which it is correlated, they should not be interpreted as outer loadings from a latent-variable PLS-SEM model. Proper empirical validation will require item-level diagnostics and an explicitly stated estimation procedure.

Explained variance. The standardized regressions generated R^2 values of 0.249 for parasocial interaction, 0.277 for perceived enjoyment, and 0.339 for impulsive buying. These numbers describe within-dataset regression fit. Their magnitude should not be interpreted as

the amount of consumer impulse purchasing explained in the market. When actual field observations become available, the complete model should be re-estimated and compared with credible alternative specifications.

Paths related to parasocial interaction and enjoyment. The generated coefficients from social attraction to parasocial interaction (β = 0.377; t = 7.504) and content characteristics to parasocial interaction (β = 0.260; t = 4.538) were both positive. Product relevance related positively to enjoyment (β = 0.321; t = 6.057), as did parasocial interaction (β = 0.341; t = 6.368). These results simply demonstrate the expected direction for the relationships built into the constructed statistical exercise; they cannot validate prior theories about AI presenters (Li et al., 2025; Kim et al., 2026).

Impulse-purchase paths. Parasocial interaction (β = 0.298; t = 5.380) and perceived enjoyment (β = 0.343; t = 6.573) both had positive associations with the constructed impulsive-buying score. The sale-proneness control had β = 0.119 (t = 2.198). The coefficient magnitudes are specific to the generation mechanism and the regression specification, not estimates of effects among real online shoppers. Their interpretation must remain conditional on the synthetic nature of the observations.

Moderation analysis. The standardized PE × SP product term was positively associated with the synthetic IB score (β = 0.131; t = 2.512; p = 0.013). In substantive consumer research, a positive interaction would mean that a larger sale-proneness score corresponds to a steeper enjoyment–buying slope. Here that pattern is not a discovered market relationship; the synthetic data-generation process was designed to contain a modest interaction. A valid field study should estimate confidence intervals, simple slopes, and robustness checks from observed participant data.

Mediation Analysis

Table 6. Indirect Effect Test Results

Relationship	β	Bootstrap SE	95% CI Lower	95% CI Upper
PSI → PE → IB	0.117	0.027	0.067	0.173

Source: 1,200 bootstrap resamples from the constructed dataset (N = 260).

Indirect association. The estimated PSI → PE → IB product of regression paths was 0.117, with a percentile 95% bootstrap interval of [0.067, 0.173]. This result shows how the mediation statistic is computed. It is not evidence that enjoyment mediates the effect of parasocial interaction in a real consumer population. Moreover, mediation observed in a cross-sectional survey is associative unless stronger temporal and causal assumptions can be defended.

Discussion and practical relevance. The framework organizes AI shopstreaming into three kinds of external stimulus, two internal consumer responses, and an impulse-buying outcome, while allowing sale proneness to condition the enjoyment–buying association. Previous scholarship on AI-powered virtual idols, influencer relationships, and livestream enjoyment supports examining these connections (Li et al., 2025; Karahan, 2025; Zhu & Vijayan, 2025). The reporting exercise does not independently establish that the hypothesized associations occur in the market. Its value is methodological: it clarifies what evidence will be needed to

distinguish platform-driven attention from genuine social connection and from a purchasing decision that was not planned before the stream.

The framework also raises a managerial question about responsible persuasion. AI-driven personalization may improve the relevance of information, yet responsive virtual hosts and promotional messaging can make purchasing feel unusually immediate. Businesses should therefore consider both conversion outcomes and the clarity of AI disclosures, particularly when shoppers may believe that a generated presenter has independent intentions or personal familiarity with them. Transparent descriptions of promotional terms and unobtrusive opportunities to reconsider a purchase are compatible with engaging livestream design. These points are managerial implications to be evaluated, not findings established by the present numerical exercise. Future empirical work can test whether disclosed AI use changes perceived social attraction, whether outcomes differ by product category, and whether enjoyment converts to impulse purchases differently across sale-proneness levels. Such extensions would build on the seven-construct core without treating every feature of a livestream platform as a separate explanatory variable.

CONCLUSIONS AND SUGGESTIONS

This manuscript develops a compact seven-construct framework for understanding potential pathways to impulsive buying in AI-powered shopstreaming. The framework differentiates product relevance, social attraction, and content characteristics from the two proposed psychological mechanisms, parasocial interaction and perceived enjoyment. Sale proneness is treated as a moderator of the enjoyment-to-impulsive-buying relationship, while its main effect is controlled in the regression. The developed structure follows prior research on AI-mediated influence and live commerce while avoiding unnecessary indicators and a conceptual-model figure.

The strongest contribution of the proposed design is the separation of perceived social connection from shopping enjoyment in a technologically mediated context. Its principal limitation at this stage is empirical: participants' exposure, measurement quality, and purchasing behavior have not yet been observed. The reported calculations demonstrate the mechanics of a reporting structure but cannot justify managerial predictions, population claims, or acceptance of the hypotheses. A subsequent field study should state the platform and AI features examined, document the sample and questionnaire, and report the selected estimator without substituting descriptive composites for latent-variable output. This distinction should remain visible when the article is prepared for editorial review.

The accompanying numeric exercise verifies the construction of reliability summaries, regression paths, bootstrap confidence intervals, moderation, and indirect-effect tables using synthetic data. It does not establish that any hypothesis is supported by respondents or that AI-powered shopstreaming causes buying impulses. To prepare this as a publishable empirical manuscript, the authors must collect authentic eligible consumer responses, verify measurement validity, analyze the realized data using a method appropriate to their hypotheses, and revise the abstract, results, and conclusion accordingly.

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