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How Live-Streaming Shopping Features Shape Consumer Purchase Intention in Guangdong Province: The Mediating Role of Customer Perceived Value and the Moderating Role of Anticipated Regret

Jun Guo [1], **Weixiang Gan** [2,*], **Tara Ahmed Mohammed** [1], **Mengfei Xiao** [1], **Jialin Liu** [3]

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Abstract: Live-streaming shopping has become one of the fastest-growing retail formats in China, yet prior research has often examined isolated platform features rather than the broader configuration of stimuli that structure consumer judgement in real time. This study compresses the original doctoral thesis into a journal-style article and investigates how six live-streaming shopping features—*interactivity, visualization, entertainment, professionalism, real-time nature, and sociability*—influence consumer purchase intention in Guangdong Province. Drawing on the Stimulus–Organism–Response framework, Perceived Value Theory, and Regret Theory, the study tests customer perceived value as a mediator and anticipated regret as a moderator. A quantitative cross-sectional survey generated 498 valid responses from Guangdong consumers with recent live-streaming shopping experience, and the model was estimated with PLS-SEM using SmartPLS 4.1. The results show that all six features have significant positive effects on purchase intention, with professionalism producing the strongest direct effect ($\beta = 0.141$, $p < 0.001$), followed by interactivity ($\beta = 0.131$, $p = 0.001$) and visualization ($\beta = 0.128$, $p = 0.001$). Customer perceived value partially mediates all six relationships, with indirect effects ranging from 0.029 to 0.047. The structural model explains 54.5% of the variance in purchase intention and 49.4% of the variance in customer perceived value, with strong predictive relevance ($Q^2 = 0.431$ and 0.367, respectively). Anticipated regret significantly weakens the positive effect of customer perceived value on purchase intention ($\beta = -0.140$, $p < 0.001$); conditional effects further show that the value–intention link becomes non-significant at high levels of anticipated regret but becomes substantially stronger at low levels. The article contributes by offering a disaggregated account of feature effects, clarifying the mediating role of perceived value, and revealing a threshold-like moderating role of anticipated regret in a collectivist, socially dense digital marketplace. Managerially, the findings indicate that stronger host expertise, richer interaction, clearer visualization, and regret-reduction mechanisms are pivotal for improving conversion efficiency in Guangdong's live-streaming commerce market.

Keywords: Live-streaming shopping; Purchase intention; Customer perceived value; Anticipated regret

Introduction

Live-streaming shopping has moved from an experimental channel to a mainstream retail infrastructure. China's live-streaming e-commerce user base reached 530 million

[1] Graduate School of Business, SEGi University, Kota Damansara, Petaling Jaya, Selangor 47810, Malaysia; [2] Zhenguigu Technology Co., Ltd., Guangyang District, Langfang, Hebei 065000, China; [3] Taylor's University, No. 1, Jalan Taylor's, 47500 Subang Jaya, Selangor, Malaysia.
* Corresponding author. Email: Gabriel1995@qq.com.

Table 1 | Scale of live-streaming e-commerce users in China, June 2021 to June 2023

Time	User Scale (100 million people)	Share of online shopping users (%)
06 / 2021	3.8	47.3
12 / 2021	4.6	55.1
06 / 2022	4.7	55.8
12 / 2022	5.2	60.9
06 / 2023	5.3	59.5

Table 2 | Transaction scale and year-on-year growth of China's live-streaming e-commerce market, 2017-2023

Year	Transaction scale (billion yuan)	Year-on-year growth
2017	196.4	-
2018	1,354.1	588.87%
2019	4,437.5	227.06%
2020	12,850.0	189.00%
2021	23,615.1	83.98%
2022	35,000.0	48.26%
2023	49,168.0	40.48%

Table 3 | Enterprise participation in China's live-streaming e-commerce industry, 2018–2023

Year	Enterprise scale (companies)	Year-on-year growth
2018	3,545	-
2019	5,684	60.31%
2020	7,502	32.01%
2021	15,900	111.94%
2022	18,700	17.67%
2023	24,000	28.34%

by June 2023, representing 59.5% of all online shoppers, while industry transaction value expanded to 49,168 billion yuan in 2023 and the number of participating enterprises rose to 24,000 (China Internet Network Information Center, 2023; iResearch Consulting Group, 2023; China E-commerce Live Streaming Report, 2022). The format does more than add video to e-commerce. It combines synchronous communication, product demonstration, host performance, social interaction, and instant purchasing opportunities within a single interface, thereby collapsing information search, affective engagement, and behavioral choice into one highly compressed decision environment (Cai et al., 2018; Wongkitrungrueng & Assarut, 2020; Xu, Huang, & Wang, 2020).

This transformation matters theoretically because live-streaming commerce cannot be adequately understood through static website logic alone. Traditional online shopping depends heavily on text, images, and deferred evaluation, whereas live-streaming settings expose consumers to richer stimuli that are immediate, interactive, and socially visible. Research has accordingly shown that digital retail responses are shaped by the environment in which information is encountered, the internal value or affective states that follow, and the behavioural tendencies those states produce (Mehrabian & Russell, 1974; Jacoby, 2002; Huang, Zhang, & Liu, 2021). Yet within the live-streaming literature, many studies still treat platform features as broad bundles or focus on only one or two dimensions, such as interactivity or vividness, without systematically comparing how a wider set of features operates together (Liang, Xu, & Wu, 2020; Xu, Wu, & Li, 2020).

As shown in **Table 1**, China's live-streaming e-commerce user base expanded from 380 million in June 2021 to 530 million in June 2023, while its share of online shopping users rose from 47.3% to 59.5%. These figures justify treating live-streaming shopping as a mainstream retail environment rather than a marginal promotional channel.

Table 2 further demonstrates the rapid commercial expansion of China's live-streaming e-commerce market. The transaction scale increased from 196.4 billion yuan in 2017 to 49,168.0 billion yuan in 2023. Although the year-on-year growth rate gradually slowed after the early explosive stage, the market continued to expand at a substantial pace, indicating that live-streaming commerce has entered a more mature but still strongly growing phase.

Table 3 shows that enterprise participation in China's live-streaming e-commerce industry rose from 3,545 companies in 2018 to 24,000 companies in 2023. This increase suggests that live-streaming shopping has become an institutionalized commercial format adopted by a growing number of firms, rather than a temporary marketing experiment limited to a small group of digital retailers.

The practical stakes are equally significant. Guangdong is one of the most commercially advanced provinces in China, with strong purchasing power, dense digital infrastructure,

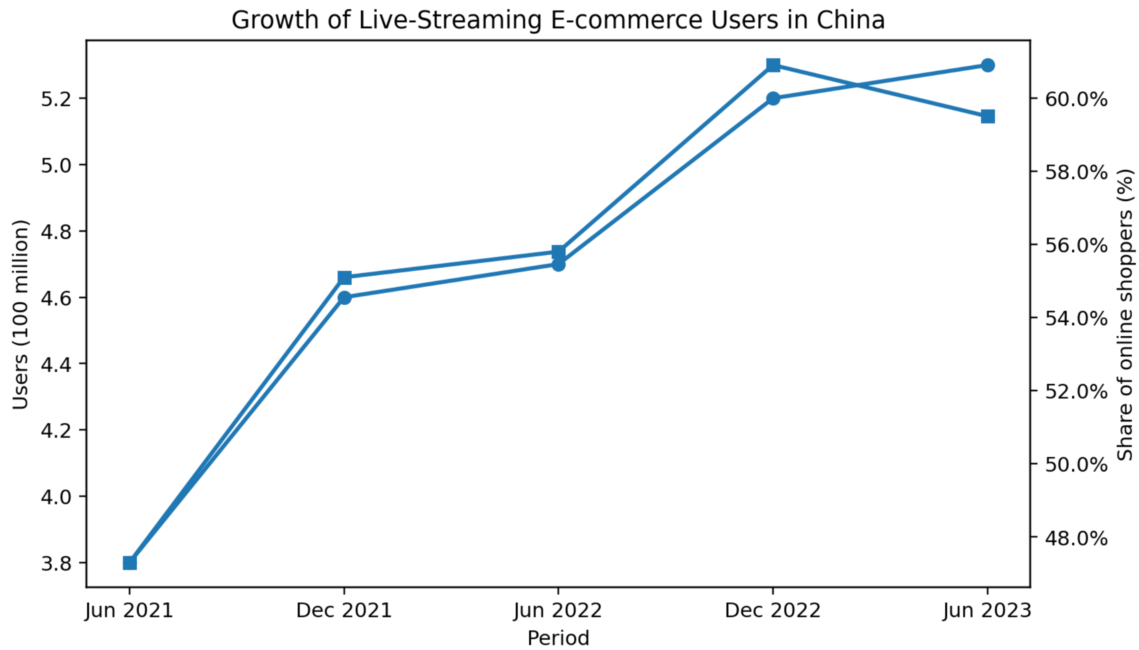

Figure 1 | Growth of live-streaming e-commerce users and the share of online shoppers in China

and mature social commerce habits (National Bureau of Statistics of China, 2022; China Internet Network Information Center, 2023). At the same time, the province exemplifies the contradictions of the live-streaming economy: consumers are highly engaged, but complaint rates, counterfeit concerns, and post-purchase dissatisfaction remain visible. In this context, understanding which live-streaming features most strongly encourage purchase intention is not a matter of incremental optimization; it is a direct response to the conversion inefficiencies that continue to confront merchants, hosts, and platforms operating in an increasingly crowded market. Guangdong thus provides an analytically fertile setting for examining not only whether feature effects exist, but also how consumers transform those feature perceptions into purchase intentions under conditions of uncertainty and social pressure.

A second gap concerns mechanism. Purchase intention rarely emerges directly from environmental cues. Consumers first interpret those cues, form utility assessments, and weigh what they receive against what they give up. Perceived value research has long argued that purchase behavior depends on the balance of benefits and sacrifices, whether functional, emotional, or social (Bolton & Drew, 1991; Woodruff, 1997; Sweeney & Soutar, 2001). Even so, the mediating role of customer perceived value remains underdeveloped in live-streaming commerce research, where studies often highlight trust, engagement, or enjoyment while leaving the value-construction process undertheorised. This omission is consequential because live-streaming features differ in the type of value they are likely to generate. Visualization may reduce uncertainty and heighten functional value; sociability may enrich social value; entertainment may raise emotional value; and professionalism may strengthen the perceived worth of product claims. Without placing perceived value at the centre of analysis, it is difficult to explain how these distinct features converge into a single purchasing judgement.

A third gap concerns boundary conditions. Live-streaming shopping is a setting in which consumers face time pressure, visible participation by others, and a steady stream of cues that may both attract and unsettle. Regret Theory suggests that anticipated negative emotion shapes decision-making before outcomes materialize, but the live-streaming literature has rarely examined how anticipated regret conditions the translation of favorable value perceptions into purchase intention (Bell, 1982; Loomes & Sugden, 1982; Zeelenberg, van der Pligt, & de Vries, 2000). This neglect is especially problematic in Guangdong, where the social density of consumption and the prevalence of impulse-inducing tactics may cause consumers to oscillate between two anxieties: regretting a poor purchase and regretting a missed opportunity. If anticipated regret becomes sufficiently salient, it may disrupt the normal cognitive pathway through which perceived value generates purchase intention.

Against this background, the present article asks three linked questions. First, how do six live-streaming shopping features influence purchase intention? Second, does customer perceived value mediate these effects? Third, does anticipated regret moderate the relationship between customer perceived value and purchase intention? By answering these questions with data from 498 consumers in Guangdong Province, the article makes three contributions. It offers a disaggregated analysis of live-streaming features within one integrated framework, clarifies the mediating

Table 4 | Integration of theoretical frameworks in the research model

Theoretical framework	Primary contribution	Research model component	Application in this study
Stimulus–Organism–Response	Overall explanatory structure	Entire model	Positions six live-streaming features as stimuli, perceived value as organism, and purchase intention as response.
Perceived Value Theory	Explains internal evaluation	Mediator	Explains how functional, emotional, and social benefits convert feature perceptions into purchase intentions.
Regret Theory	Explains boundary conditions	Moderator	Explains how anticipated regret weakens or strengthens the translation of perceived value into purchase intention.

role of customer perceived value, and demonstrates that anticipated regret can act less as a marginal dampener than as a threshold-like barrier in high-engagement digital shopping contexts. The remainder of the paper develops the theoretical model, describes the research design, reports the empirical results, and discusses the theoretical and managerial implications.

Guangdong is theoretically useful because it combines scale with complexity. It is not merely a large market; it is a market in which digital adoption, social commerce routines, and consumption sophistication are all highly developed. Consumers in such environments are likely to be more discriminating, more accustomed to comparing platforms, and more sensitive to the credibility of hosts and the emotional consequences of fast purchase decisions. For that reason, Guangdong offers more than a convenient field site. It provides a demanding empirical test for a model that links live-streaming features, value formation, and anticipated regret.

Theoretical Background and Hypotheses Development

The study is anchored in the Stimulus–Organism–Response (S–O–R) framework. Originally developed in environmental psychology, the model proposes that environmental stimuli affect behavior by first shaping internal organismic states rather than by producing direct, mechanical responses (Mehrabian & Russell, 1974). In consumer research, this insight has been used to explain how atmospheric, technological, and social cues influence cognition, affect, and purchasing behavior (Jacoby, 2002; Huang et al., 2021). In the present context, the six live-streaming shopping features constitute the stimulus layer, customer perceived value represents the organismic state, and purchase intention constitutes the behavioral response. This mapping is analytically useful because live-streaming shopping exposes consumers to simultaneous informational, affective, and social cues, making it unlikely that purchase intention arises from any single input in isolation.

Perceived Value Theory deepens the organismic layer by specifying how consumers interpret and evaluate what they experience. Classical work defines perceived value as an overall assessment based on what is received relative to what is sacrificed (Bolton & Drew, 1991; Woodruff, 1997). Later multidimensional formulations argue that consumers weigh not only functional utility but also social and emotional returns from the consumption experience (Sheth, Newman, & Gross, 1991; Sweeney & Soutar, 2001). This is particularly relevant in live-streaming commerce. Consumers may perceive value because they obtain credible information, because the session is enjoyable, because they feel recognized by the host, or because the interaction provides social validation. Accordingly, perceived value is treated here not as a vague attitudinal residue but as the central psychological mechanism through which live-streaming features become behaviorally consequential.

Regret Theory contributes the final element of the framework by clarifying why the same favorable value judgement may not always produce the same behavioral intention. Decision-makers do not evaluate options purely in terms of expected utility; they also anticipate the emotional consequences of choosing incorrectly or failing to choose at all (Bell, 1982; Loomes & Sugden, 1982). Anticipated regret enters consumer choice through counterfactual thinking: consumers imagine the better or worse worlds that may follow their decision, and those imagined futures alter present action (Markman, 1995; Zeelenberg et al., 1996; Zeelenberg & Pieters, 2007). In live-streaming shopping, this mechanism is amplified by scarcity cues, flash discounts, social proof, and rapid host persuasion. Anticipated regret therefore offers a theoretically compelling explanation for why perceived value sometimes translates efficiently into purchase intention and sometimes does not.

Table 4 clarifies how the three theoretical frameworks are integrated into the research model. The Stimulus–Organism–Response framework provides the overall explanatory structure, Perceived Value Theory explains the internal evaluative mechanism, and Regret Theory explains the boundary condition under which perceived value is more or less likely to translate into purchase intention. This theoretical integration supports the model's direct, mediating, and moderating logic.

The first substantive relationship concerns interactivity. Live-streaming differs from ordinary online retail because consumers can ask questions, request demonstrations, and receive immediate responses while still in the evaluative stage of decision-making. From an S–O–R perspective, interactivity intensifies social presence and reduces psychological distance between seller and buyer (Short, Williams, & Christie, 1976; Kang, Lu, Guo, et al., 2021). It also reduces information asymmetry by allowing product claims to be clarified in real time. Prior studies show that interactive live-streaming environments elevate consumer engagement and trust, thereby enhancing the willingness to proceed toward purchase (Wongkitrungrueng & Assarut, 2020; Xu, Huang, & Wang, 2020). On this basis, interactivity should have a positive direct effect on purchase intention.

Visualization is equally central. Consumers cannot physically inspect products online, so visual richness becomes a substitute for tactile experience and an important route to uncertainty reduction. When products are shown from different angles, used in realistic situations, or demonstrated on camera, consumers gain a more concrete impression of quality, usability, and fit. Such features are likely to raise both functional value and behavioral confidence. Existing live-streaming studies likewise indicate that vivid, concrete product presentation encourages more favorable attitudes and stronger purchase evaluations by making the shopping environment more intelligible and believable (Chen & Zhang, 2021; Xu, Wu, & Li, 2020). Visualization should therefore positively influence purchase intention.

Entertainment, though sometimes treated as a peripheral hedonic bonus, is more structurally important than that assumption implies. Live-streaming sessions often blend commerce with humour, play, host charisma, games, and emotionally engaging performance. These elements can lengthen viewing time, sustain attention, and create a pleasurable consumption context that consumers may generalize to the products being promoted (Cai et al., 2018; Chen, Y. S., & Chang, 2013). Because emotional states affect evaluation and behavioral readiness, entertaining live sessions are likely to stimulate stronger purchase intention, even when their effect size is smaller than that of more information-oriented features.

Professionalism addresses a separate but decisive concern: credibility. Consumers entering a live-streaming room do not merely want to be excited; they also want to know whether the host can be believed. Professionalism refers to the host's product expertise, explanatory clarity, command of usage scenarios, and ability to offer convincing, specific answers. The source credibility literature suggests that expertise and trustworthiness substantially enhance persuasive effectiveness (Ohanian, 1990). In live-streaming commerce, professionalism may be especially influential because consumers confront visible uncertainty over authenticity, quality, and appropriateness. A host who demonstrates product knowledge and disciplined communication can reduce perceived risk and increase purchase readiness. It is therefore reasonable to expect professionalism to positively influence purchase intention and, potentially, to outperform more entertainment-driven cues.

Real-time nature and sociability represent two further features that distinguish live-streaming from static e-commerce. Real-time nature captures immediacy: comments are answered quickly, inventory updates are visible, and purchasing opportunities appear to unfold synchronously with evaluation. This immediacy can heighten efficiency and intensify the feeling that consumers are acting within a living event rather than browsing a catalogue. Sociability, by contrast, concerns the interpersonal and communal qualities of the session: viewers observe one another, exchange opinions, share experiences, and experience shopping as a social practice rather than a solitary task. Because live-streaming commerce operates in socially visible settings, sociability may increase both belonging and reassurance, especially in collectivist cultural environments. Prior research suggests that socially embedded interaction on digital platforms affects both value perception and purchase-oriented behavior (Koo, Lee, & Lee, 2008; Roseli, Zhang, & Ahmad, 2023). Both features should therefore positively affect purchase intention.

These direct effects, however, are unlikely to tell the whole story. A richer explanation treats customer perceived value as the internal mechanism through which features become behaviorally relevant. Interactivity can create value by supplying tailored information; visualization can create value by reducing uncertainty; entertainment can create value by increasing enjoyment; professionalism can create value by strengthening confidence in product claims; real-time nature can create value by enabling quick, efficient evaluation; and sociability can create value by producing social reassurance and shared experience. If consumers interpret the live-streaming environment as genuinely useful, enjoyable, trustworthy, and socially meaningful, then purchase intention should rise. The logic is consistent with value-based consumer models and with emerging live-streaming research that identifies value as a key psychological bridge between technological features and behavioral outcomes (Li et al., 2021; Xu, Wu, & Li, 2020). Accordingly, customer perceived value is expected to mediate the effects of all six live-streaming features on purchase intention.

Anticipated regret introduces a more nuanced boundary condition. Consumers may judge a live-streaming session positively and still hesitate because they fear buying the wrong product, overpaying, or missing a better offer elsewhere. Conversely, when regret anticipation is low, consumers may convert favorable value perceptions into intention more readily because the emotional cost of deciding is lower. Regret Theory therefore suggests a negative moderating effect overall: as anticipated regret rises, the positive relationship between perceived value and purchase intention should weaken (Bell, 1982; Zeelenberg et al., 2000). Yet live-streaming settings also complicate this prediction because upward and downward regret may coexist. The same consumer may simultaneously fear making a bad purchase and missing a scarce opportunity. The present study tests this moderation empirically and anticipates that, at minimum, low anticipated regret should strengthen the value–intention relationship.

The conceptual model emerging from this review integrates direct, indirect, and contingent relationships within a single framework. Six live-streaming shopping features are specified as exogenous predictors of purchase intention, customer perceived value is specified as a mediator, and anticipated regret is specified as a moderator of the perceived

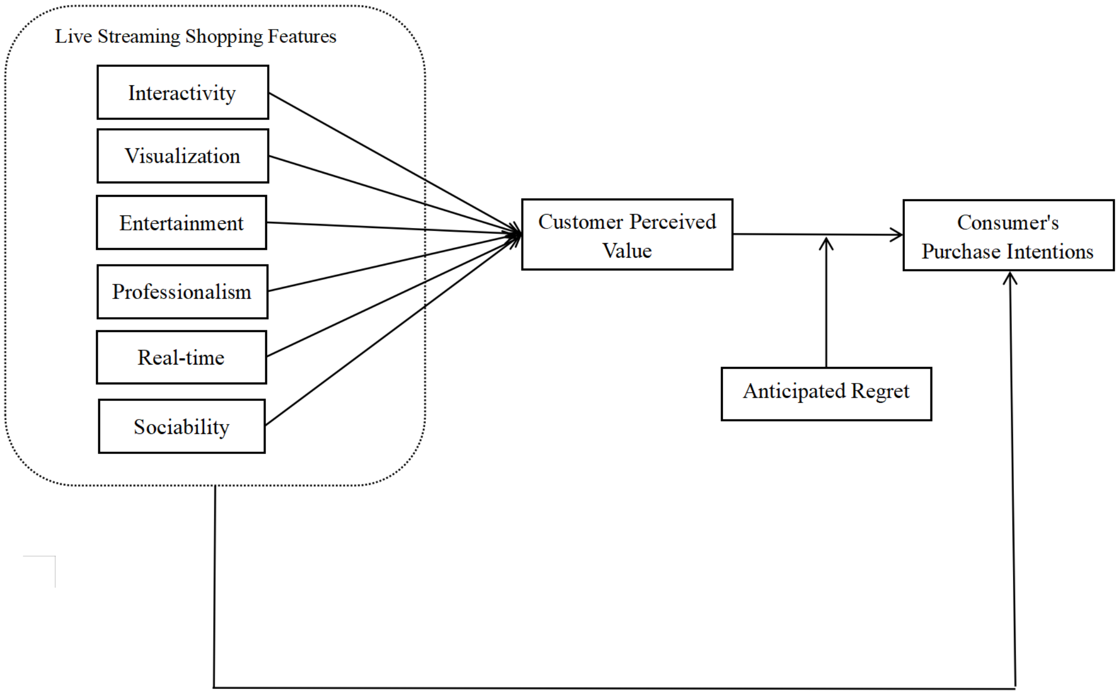

Figure 2 | Conceptual framework

value–purchase intention link. This architecture responds directly to the three gaps motivating the article: insufficient disaggregation of live-streaming feature effects, inadequate theorization of the value-formation mechanism, and limited attention to emotional boundary conditions. It also offers a model with clear explanatory and practical value: it shows not merely whether features matter, but how and under what conditions they matter.

Sociability warrants additional conceptual attention because it captures one of the most distinctive departures from pre-social forms of home shopping. Television shopping was persuasive but largely one-directional. Live-streaming commerce, by contrast, allows consumers to watch others react, to observe collective enthusiasm or doubt, and to contribute to the evolving tone of the session. In such settings, purchase intention can be strengthened not only by information but also by social confirmation. This is particularly important in collectivist markets where individuals often interpret purchase decisions through relational cues and public legitimacy rather than through isolated utility calculations. Sociability should therefore be understood as both a platform feature and a social-value generator (Short et al., 1976; Roseli et al., 2023).

Entertainment also deserves a more careful reading than the usual hedonic–utilitarian dichotomy permits. In live-streaming settings, entertainment can serve instrumental as well as affective purposes. Humour, rhythm, dramatic demonstration, or game-based interaction may keep viewers cognitively involved long enough to process product information they would otherwise ignore. Entertainment can therefore increase message receptivity, sustain cognitive engagement, and reduce the monotony associated with repeated comparison tasks. Its contribution to purchase intention may be smaller than that of professionalism, but it still forms part of the commercial architecture of the session rather than an optional afterthought (Cai et al., 2018; Chen, Y. S., & Chang, 2013).

The value-mediation argument is also strengthened by the multidimensionality of the live-streaming encounter. A consumer may perceive strong value because the host's explanation reduces functional uncertainty, because the lively atmosphere makes the session enjoyable, or because discussion with other viewers generates a sense of shared validation. These are not competing interpretations; they are layered evaluations that can coexist within one session. The choice to model customer perceived value as a single higher-order evaluative mechanism is therefore theoretically parsimonious and empirically useful. It allows the analysis to capture the integrative judgement consumers make after weighing informational, emotional, and social benefits together (Sheth et al., 1991; Sweeney & Soutar, 2001).

Finally, the moderation logic is not merely an add-on to the model; it is central to explaining why live-streaming commerce sometimes disappoints practitioners despite apparently favorable audience metrics. A session may be interactive, visually rich, and professionally delivered, but if consumers become too anxious about future regret, those favorable perceptions may not convert into purchase. Moderation analysis therefore moves the model closer to the realities of platform management, where the challenge is not only to create value but also to preserve the consumer's confidence that acting now will not be punished later. This is why the

Table 5 | Summary of constructs and measurement scales

Construct	Items	Original source	Adaptation source	Prior reliability	Scale
Interactivity	3	Liu (2003)	Xu & Wu (2022)	α > 0.80	7-point Likert
Visualization	4	Li & Liu (2020)	Zhang (2022)	α = 0.89	7-point Likert
Entertainment	3	Chen et al. (2020)	Lin (2022)	α = 0.85	7-point Likert
Professionalism	3	Kang (2021)	Chen & Zhang (2021)	α = 0.82	7-point Likert
Real-time nature	3	Xue (2020)	—	α = 0.88	7-point Likert
Sociability	4	Roseli et al. (2023)	—	α = 0.86	7-point Likert
Customer perceived value	4	Sweeney & Soutar (2001)	Wang et al. (2019)	α > 0.85	7-point Likert
Anticipated regret	4	Zeelenberg et al. (1996)	Lin Nan (2021)	α = 0.84	7-point Likert
Purchase intention	3	Dodds et al. (1991)	Zhao & Liu (2020)	α = 0.88	7-point Likert

Table 6 | Response rate summary

Description	Number	Percentage
Questionnaires distributed	700	100%
Non-responses and refusals	78	11.1%
Questionnaires returned	622	88.9%
Invalid responses removed	144	20.6% of distributed
Valid responses	498	71.1% of returned / 80.1% of targeted

present study treats anticipated regret as a substantive theoretical boundary condition rather than a control variable or post hoc explanation.

Research Method

The study employed a quantitative, cross-sectional design. This design is appropriate because the research questions concern the magnitude and direction of relationships among latent constructs rather than the reconstruction of personal narratives or platform ethnographies. The study is deductive in logic: hypotheses were derived from the S–O–R framework, Perceived Value Theory, and Regret Theory, and then examined empirically using structured survey data. The individual consumer was the unit of analysis, specifically a consumer located in Guangdong Province who had recent live-streaming shopping experience. Guangdong was selected because of its economic weight, advanced digital infrastructure, and relevance as a socially intensive consumption environment. These characteristics make it a strong empirical context for testing the explanatory reach of theories that were largely developed outside live-streaming and often outside China.

Data were collected through Wenjuanxing, a widely used online survey platform in China. The survey was fielded in January 2026 to avoid distortion from major shopping festivals and to capture more routine purchasing judgements. Following the original thesis design, stratified random sampling based on age and gender was used in order to improve the balance of the sample. A screening item ensured that respondents had participated in a live-streaming shopping session within the preceding three months. Of 700 distributed questionnaires, 622 were returned. After excluding 78 non-responses or refusals and removing 144 invalid cases because of patterned responses, substantial missingness, ineligibility, or implausibly short completion time, 498 valid questionnaires remained for analysis. This sample size is adequate for the complexity of the model and consistent with the requirements of variance-based structural modeling (Hair et al., 2011, 2022).

Table 5 summarizes the measurement design of the study. It shows that all constructs were operationalized using established or adapted scales from prior research, with each construct measured by multiple items on a seven-point Likert scale. This supports the methodological credibility of the questionnaire and demonstrates that the empirical model is grounded in validated measurement traditions rather than newly invented indicators.

Table 6 reports the questionnaire distribution and screening process. Of the 700 questionnaires distributed, 622 were returned, and 498 valid responses remained after removing non-responses, refusals, and invalid cases. The final valid sample represents 71.1% of all distributed questionnaires and 80.1% of returned questionnaires, indicating that the study retained a sufficiently large and usable dataset for PLS-SEM analysis.

All focal constructs were measured with multi-item reflective scales on seven-point Likert-type response formats ranging from strong disagreement to strong agreement. Interactivity, visualization, entertainment, professionalism, real-time nature, and sociability were operationalized from measurement traditions already present in the original thesis. Customer perceived value was measured as a higher-order evaluative construct representing the overall worth consumers attached to the live-streaming shopping experience, while anticipated regret captured the emotional concern that choosing, or failing to choose, could produce an unfavorable future outcome. Purchase intention reflected the likelihood of purchasing products recommended in the live-streaming room. Before the formal survey, the instrument

Table 7 | Demographic profile of respondents

Category	Profile	Frequency	Percentage (%)
Gender	Male	258	51.81
Gender	Female	240	48.19
Age	Under 18 years	44	8.84
Age	18–24 years	86	17.27
Age	25–35 years	180	36.14
Age	36–50 years	126	25.30
Age	Above 50 years	62	12.45
Education	High school and below	85	17.07
Education	Junior college	103	20.68
Education	Undergraduate	227	45.58
Education	Master's degree or above	83	16.67
Monthly income	Less than RMB 3,000	55	11.04
Monthly income	RMB 3,001–5,000	68	13.65
Monthly income	RMB 5,001–8,000	194	38.96
Monthly income	RMB 8,001–13,000	106	21.29
Monthly income	More than RMB 13,000	75	15.06
Shopping frequency	Every day	120	24.10
Shopping frequency	Every 2–3 days	177	35.54
Shopping frequency	Once a week	93	18.67
Shopping frequency	Every 2–3 weeks	61	12.25
Shopping frequency	Once a month or less	47	9.44
Average session duration	Less than 30 minutes	142	28.51
Average session duration	30–60 minutes	179	35.94
Average session duration	61–180 minutes	106	21.29
Average session duration	More than 180 minutes	71	14.26

underwent expert review, pre-test refinement, and pilot testing. The pilot stage indicated acceptable internal consistency and factor structure, supporting the decision to proceed to full data collection.

The data analysis followed a staged procedure. SPSS 27.0 was first used for data cleaning and preliminary diagnostics, including descriptive statistics, skewness and kurtosis checks, and common method bias assessment. Harman's single-factor test showed that the first extracted factor explained 34.932% of the total variance, which is below the conventional 50% threshold, suggesting that common method bias was not severe in the sample. KMO and Bartlett's test values were likewise satisfactory, supporting the factorability of the data. The main model was then estimated in SmartPLS 4.1. PLS-SEM was chosen because the model contains multiple constructs, mediation and moderation paths, and a strong predictive objective. Measurement quality was assessed through outer loadings, Cronbach's alpha, composite reliability, AVE, Fornell–Larcker, and HTMT. The structural model was assessed through bootstrapped path coefficients, confidence intervals, R^2, f^2, Q^2, and conditional effect analysis. Moderation was tested with a product-indicator approach using mean-centred indicators, and the significance tests were based on 5,000 bootstrap resamples (Anderson & Gerbing, 1988; Fornell & Larcker, 1981; Hayes, 2013; Henseler, Ringle, & Sinkovics, 2015; Hair et al., 2022).

Ethical safeguards were built into the original research design and are retained conceptually in this compressed version. Participation was voluntary, anonymity was protected, and the questionnaire focused on perceptions of platform features and shopping experiences rather than on sensitive personal data. Respondents completed the survey in a self-administered online format, reducing interviewer effects and allowing them to answer at their own pace. These design choices are important not only ethically but also methodologically, because they help reduce evaluation apprehension and the risk that socially desirable responding will contaminate measures of value perception or purchase intention.

The analytical thresholds used in the study followed established PLS-SEM practice. Outer loadings above 0.70 were treated as evidence of indicator reliability; composite reliability above 0.70 and AVE above 0.50 were treated as evidence of acceptable internal consistency and convergent validity; HTMT values below 0.85 were used to support discriminant validity; and bootstrap confidence intervals that did not include zero were treated as evidence of significant direct, indirect, or conditional effects (Fornell & Larcker, 1981; Henseler et al., 2015; Hair et al., 2022). These thresholds matter because the compressed journal article preserves only the most policy- and theory-relevant empirical outputs, and those outputs need to remain anchored in transparent analytical standards.

Data Analysis

The sample profile suggests that the study captured a commercially relevant live-streaming audience. Gender was

Table 8 | Descriptive statistics of constructs

Construct	N	Min	Max	Mean	SD
Interactivity	498	1.00	7.00	4.26	1.47
Visualization	498	1.25	7.00	4.33	1.29
Entertainment	498	1.00	7.00	4.22	1.47
Professionalism	498	1.00	7.00	4.26	1.44
Real-time	498	1.00	7.00	4.32	1.41
Sociability	498	1.00	6.50	4.25	1.32
Customer perceived value	498	1.00	6.75	4.08	1.45
Anticipated regret	498	1.25	7.00	4.35	1.35
Purchase intention	498	1.00	7.00	3.84	1.54

Table 9 | Reliability and convergent validity

Construct	Cronbach's alpha	Composite reliability	AVE
Interactivity	0.872	0.922	0.797
Visualization	0.866	0.909	0.715
Entertainment	0.872	0.921	0.796
Professionalism	0.853	0.911	0.774
Real-time	0.859	0.914	0.780
Sociability	0.868	0.910	0.718
Customer perceived value	0.892	0.925	0.756
Anticipated regret	0.867	0.909	0.714
Purchase intention	0.881	0.926	0.808

broadly balanced, with 51.81% male and 48.19% female respondents. The largest age segment was 25–35 years (36.14%), followed by 36–50 years (25.30%) and 18–24 years (17.27%). Nearly half of the respondents held an undergraduate degree, and the modal income group was RMB 5,001–8,000 per month. Engagement with live-streaming shopping was high: 59.64% reported participating at least every two to three days, and 71.49% spent more than 30 minutes in a typical shopping session. This composition is consistent with the idea that live-streaming shopping in Guangdong is no longer confined to casual browsing; it represents a substantive, recurring part of consumers' digital purchase routines.

Preliminary diagnostics did not indicate serious data-quality concerns. Skewness values ranged from -0.517 to -0.003 and kurtosis values from -1.183 to -0.665, suggesting acceptable distributional behavior for variance-based estimation. Harman's single-factor result also reduced concern that the model would be dominated by one common latent factor. Descriptive statistics further indicate that respondents evaluated visualization (M = 4.33), real-time nature (M = 4.32), interactivity and professionalism (both M = 4.26), and sociability (M = 4.25) positively, while purchase intention itself was somewhat more conservative (M = 3.84). This pattern is informative: consumers were generally receptive to live-streaming features, but favorable perceptions did not automatically translate into very high purchase intention, reinforcing the need to examine mediation and moderation.

As reported in Table 7, the sample contains a balanced gender distribution, a strong representation of consumers aged 25–35, and frequent engagement with live-streaming shopping. The demographic structure indicates that the data capture an active consumer segment rather than a weakly involved or incidental audience.

Table 8 presents the descriptive statistics for the main constructs. Respondents evaluated visualization, real-time nature, interactivity, professionalism, and sociability relatively positively, whereas purchase intention recorded a comparatively lower mean score. This pattern suggests that consumers may recognize the attractiveness of live-streaming features, but favorable feature perceptions do not automatically become strong purchase intention, which justifies the subsequent mediation and moderation analysis.

The measurement model performed well. All indicator loadings exceeded the accepted minimum of 0.70, ranging from 0.796 to 0.930, which supports item reliability. Internal consistency was also strong, with Cronbach's alpha values between 0.853 and 0.892 and composite reliability values between 0.909 and 0.926. AVE values ranged from 0.714 to 0.808, indicating that each construct explained more than half of the variance in its indicators. Together, these results support the convergent validity of the measurement model. Indicator VIF values ranged from 1.877 to 3.828 and inner-model VIF values from 1.303 to 2.036, remaining comfortably below common critical thresholds and suggesting that multicollinearity did not threaten estimation stability.

Discriminant validity was likewise supported. In the Fornell–Larcker matrix, the square root of AVE for each construct exceeded its correlations with the remaining constructs. The HTMT ratios ranged from 0.132 to 0.685, remaining below the conventional 0.85 ceiling. The measurement model therefore provides a sound basis for structural interpretation. Figure 3 reproduces the original thesis mea-

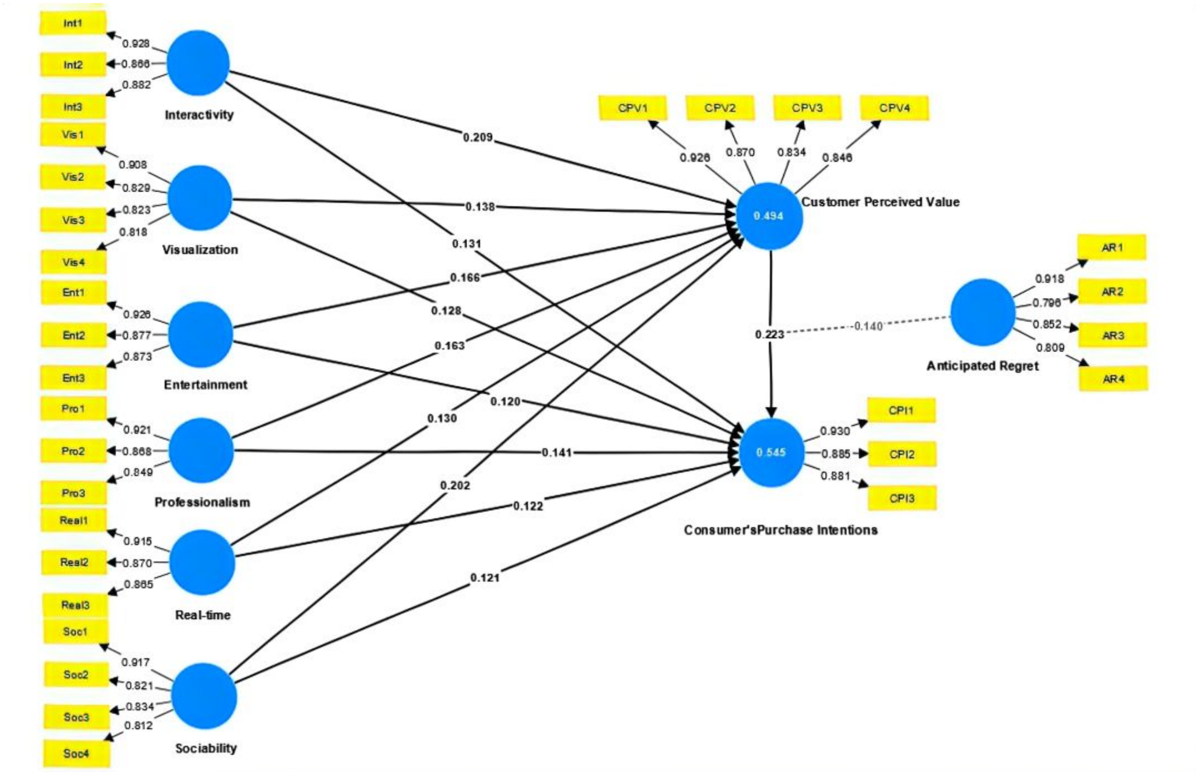

Figure 3 | Measurement model assessment results with factor loadings, reliability, and convergent validity

surement-model visualization, while Tables 9-11 report the key reliability and validity indicators retained in the compressed journal version.

Table 9 reports the reliability and convergent validity results. Cronbach's alpha values range from 0.853 to 0.892, composite reliability values range from 0.909 to 0.926, and AVE values range from 0.714 to 0.808. These results exceed commonly accepted thresholds, indicating that the constructs have strong internal consistency and satisfactory convergent validity.

Table 10 presents the Fornell–Larcker discriminant validity results. The square root of AVE for each construct is higher than its correlations with other constructs, suggesting that the latent variables are empirically distinct. This supports the claim that customer perceived value, anticipated regret, purchase intention, and the six live-streaming shopping features capture different conceptual domains.

Table 11 further confirms discriminant validity using the HTMT criterion. All HTMT ratios remain below the conservative threshold of 0.85, indicating that the constructs are not excessively overlapping. This provides additional evidence that the measurement model is suitable for interpreting the structural relationships among the variables.

The structural model confirms that all six live-streaming shopping features exert significant positive direct effects on purchase intention. Professionalism is the strongest predictor ($\beta = 0.141$, $p < 0.001$), followed by interactivity ($\beta = 0.131$, $p = 0.001$), visualization ($\beta = 0.128$, $p = 0.001$), real-time nature ($\beta = 0.122$, $p = 0.001$), sociability ($\beta = 0.121$, $p = 0.001$), and entertainment ($\beta = 0.120$, $p = 0.001$). The relatively narrow spread of coefficients suggests that live-streaming effectiveness is multidimensional: no single feature alone determines purchase intention, but some features matter more than others. The prominence of professionalism indicates that consumers in Guangdong weigh expertise and credible explanation slightly more heavily than pure enjoyment when deciding whether to buy.

Customer perceived value partially mediates all six feature–purchase intention relationships. The indirect effects range from 0.029 for real-time nature to 0.047 for interactivity, with all confidence intervals excluding zero and all p-values below 0.01. Interactivity and sociability display especially meaningful indirect pathways, suggesting that live-streaming's relational qualities are behaviorally important not simply because they are pleasant, but because they alter the consumer's evaluation of what the session and its products are worth. The partial rather than full mediation pattern is theoretically revealing. It implies that customer perceived value is a critical pathway, but not the only one. Some portion of the direct feature effect remains outside the value mechanism, leaving room for additional processes such as trust, affective arousal, or para-social attachment.

Model fit in PLS-SEM is evaluated primarily through explanatory and predictive criteria, and on these terms the model performs well. The predictors explain 54.5% of the variance in purchase intention and 49.4% of the variance in

Table 10 | Discriminant validity: Fornell–Larcker criterion

	AR	CPI	CPV	Ent	Int	Pro	Real	Soc	Vis
AR	0.845								
CPI	-0.262	0.899							
CPV	-0.279	0.870	0.870						
Ent	-0.117	0.466	0.467	0.892					
Int	-0.130	0.510	0.526	0.380	0.893				
Pro	-0.216	0.511	0.497	0.370	0.433	0.880			
Real	-0.144	0.448	0.429	0.348	0.318	0.316	0.883		
Soc	-0.207	0.509	0.518	0.317	0.437	0.424	0.371	0.847	
Vis	-0.239	0.491	0.473	0.376	0.390	0.407	0.351	0.394	0.845

Abbreviations: AR = anticipated regret; CPI = purchase intention; CPV = customer perceived value; Ent = entertainment; Int = interactivity; Pro = professionalism; Real = real-time; Soc = sociability; Vis = visualization

Table 11 | Discriminant validity: HTMT ratios

Construct	AR	CPI	CPV	Ent	Int	Pro	Real	Soc	Vis
AR									
CPI	0.290								
CPV	0.311	0.685							
Ent	0.132	0.531	0.529						
Int	0.141	0.581	0.596	0.434					
Pro	0.248	0.589	0.570	0.429	0.502				
Real	0.160	0.513	0.489	0.401	0.365	0.368			
Soc	0.229	0.582	0.587	0.365	0.501	0.493	0.428		
Vis	0.273	0.561	0.539	0.434	0.448	0.474	0.406	0.455	

customer perceived value. These figures indicate moderate to substantial explanatory power for a consumer-behavior model with multiple perceptual antecedents. Effect sizes for the individual predictors are small, but consistently meaningful, which is common in models where several correlated stimuli jointly contribute to an outcome. Predictive relevance is also strong, with Q^2 values of 0.431 for purchase intention and 0.367 for customer perceived value, suggesting that the model retains out-of-sample predictive usefulness rather than merely fitting the observed data. Figure 4 and Tables 12–16 report the main structural results preserved from the original thesis.

The moderation analysis adds a further layer of interpretation. Customer perceived value has a significant positive effect on purchase intention in the presence of the interaction term ($\beta = 0.223$, $p < 0.001$), but the interaction between anticipated regret and customer perceived value is negative and significant ($\beta = -0.140$, $p < 0.001$). This indicates that as anticipated regret increases, the behavioral force of perceived value weakens. Conditional effects clarify the pattern. At low levels of anticipated regret, the effect of customer perceived value on purchase intention is strong and significant ($\beta = 0.379$, $p < 0.001$). At the mean level, the effect remains significant but weaker ($\beta = 0.230$, $p < 0.001$). At high levels, however, the relationship becomes statistically nonsignificant ($\beta = 0.082$, $p = 0.182$). This finding is not a mere variation in slope; it suggests that once regret anticipation becomes sufficiently salient, favorable value perceptions cease to be enough to generate purchase intention.

More detailed inspection of the measurement diagnostics reinforces the robustness of the instrument. Loadings for customer perceived value ranged from 0.834 to 0.926, for purchase intention from 0.881 to 0.930, and for anticipated regret from 0.796 to 0.918, indicating that the items retained in the model are strongly tied to their latent constructs. This matters because the study compresses a full doctoral thesis into article form: retaining precise indicator evidence ensures that the shorter version does not obscure the psychometric quality underpinning the substantive claims. The results suggest that the instrument is sufficiently stable to serve future work examining comparable live-streaming environments.

The validity evidence is also theoretically consistent with the model's architecture. Customer perceived value correlates positively with purchase intention and all six features, but the discriminant validity results show that it remains empirically distinct from them. In other words, consumers do not simply report perceived value as another name for liking interactivity or visualization. They appear to aggregate those cues into a higher-order judgement that is related to, but not reducible to, any single feature. This is exactly what the mediation framework assumes. Likewise, anticipated regret is negatively associated with purchase intention and customer perceived value, but it is not redundant with either of them, which strengthens the interpretation of regret as a boundary condition rather than a substitute mediator.

The direct-effect pattern is noteworthy not only because every coefficient is significant, but also because the coeffi-

Table 12 | Direct effect results

Hypothesis	Path	β	t	p	2.5%	97.5%
H1a	Interactivity → Purchase intention	0.131	3.475	0.001	0.054	0.203
H1b	Visualization → Purchase intention	0.128	3.399	0.001	0.053	0.201
H1c	Entertainment → Purchase intention	0.120	3.223	0.001	0.049	0.193
H1d	Professionalism → Purchase intention	0.141	3.682	0.000	0.065	0.216
H1e	Real-time → Purchase intention	0.122	3.367	0.001	0.053	0.195
H1f	Sociability → Purchase intention	0.121	3.221	0.001	0.046	0.195

Table 13 | Indirect effect results (mediation)

Hypothesis	Path	β	t	p	2.5%	97.5%	Result
H2a	Interactivity → CPV → Purchase intention	0.047	3.429	0.001	0.022	0.076	Supported
H2b	Visualization → CPV → Purchase intention	0.031	2.642	0.008	0.010	0.055	Supported
H2c	Entertainment → CPV → Purchase intention	0.037	3.064	0.002	0.016	0.062	Supported
H2d	Professionalism → CPV → Purchase intention	0.036	3.119	0.002	0.015	0.060	Supported
H2e	Real-time → CPV → Purchase intention	0.029	2.843	0.004	0.011	0.050	Supported
H2f	Sociability → CPV → Purchase intention	0.045	3.335	0.001	0.021	0.074	Supported

Table 14 | Variance explained (R^2)

Endogenous variable	R^2	Adjusted R^2
Purchase intention	0.545	0.537
Customer perceived value	0.494	0.488

Table 15 | Effect sizes (f^2)

Relationship	f^2	Effect size
CPV → Purchase intention	0.053	Small
Entertainment → Purchase intention	0.022	Small
Entertainment → CPV	0.040	Small
Interactivity → Purchase intention	0.024	Small
Interactivity → CPV	0.059	Small
Professionalism → Purchase intention	0.029	Small
Professionalism → CPV	0.036	Small
Real-time → Purchase intention	0.024	Small
Real-time → CPV	0.026	Small
Sociability → Purchase intention	0.021	Small
Sociability → CPV	0.055	Small
Visualization → Purchase intention	0.024	Small
Visualization → CPV	0.026	Small

Table 16 | Predictive relevance (Q^2)

Endogenous variable	Q^2
Purchase intention	0.431
Customer perceived value	0.367

cients are relatively balanced. This is consistent with the argument that live-streaming shopping is configurational in practice: consumers do not need only one thing from a session. They need product clarity, credible explanation, social validation, and a sufficient degree of enjoyment to remain attentive. The coefficient pattern therefore supports a portfolio interpretation of platform design. Merchants who overinvest in one feature while neglecting the others may fail to realize the combined stimulus environment that actually drives purchase intention.

The moderation findings can be translated into substantive behavioral language. When anticipated regret is low, value judgements are actionable; consumers feel able to trust their positive evaluations. When anticipated regret reaches average levels, value still matters, but its behavioral force declines. When anticipated regret becomes high, however, the decision environment changes qualitatively. Consumers no longer appear to ask, 'Is this good value?' but rather, 'What if acting now turns out badly?' That shift from evaluative to defensive processing helps explain why high perceived value is not always sufficient to trigger purchase in live-streaming settings characterized by urgency and public visibility.

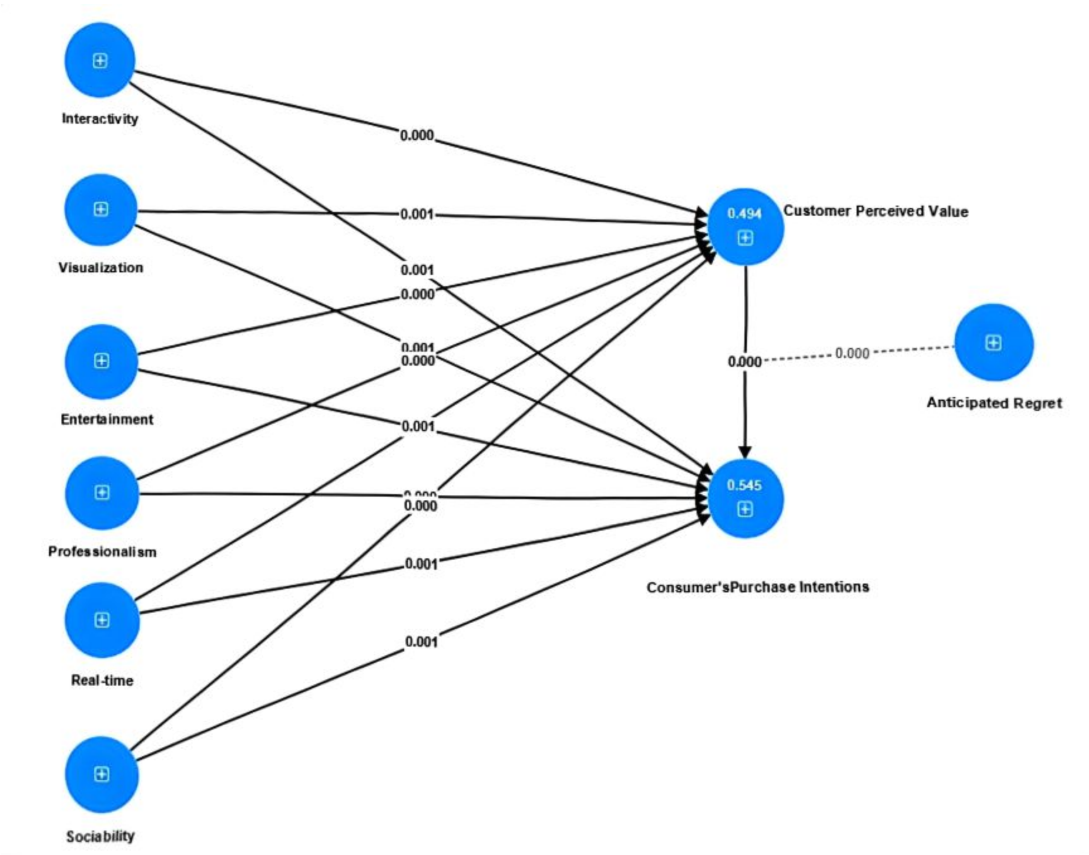

Figure 4 | Structural model results with path coefficients for the impact of live-streaming features on purchase intention

Table 17 presents the moderation test. Customer perceived value has a significant positive effect on purchase intention, while the interaction term between anticipated regret and customer perceived value is negative and significant. This indicates that anticipated regret weakens the positive relationship between perceived value and purchase intention.

Table 18 reports the conditional effects of customer perceived value on purchase intention at different levels of anticipated regret. When anticipated regret is low, the effect of customer perceived value on purchase intention is strong and significant. At the mean level, the effect remains significant but weaker. At high levels of anticipated regret, the effect becomes non-significant. This suggests that high anticipated regret can interrupt the normal conversion of perceived value into purchase intention.

Table 19 summarizes the hypothesis-testing results. The findings show that all six direct-effect hypotheses and all six mediation hypotheses are supported. For the moderation hypotheses, low anticipated regret strengthens the customer perceived value–purchase intention relationship, while high anticipated regret does not produce a significant positive conditional effect. This summary confirms that the model is empirically supported in its direct and mediating paths, while the moderation results reveal a more nuanced emotional boundary condition.

Discussion

The first major conclusion of the study is that live-streaming shopping works through a portfolio of features rather than a single dominant platform attribute. The positive effects of interactivity, visualization, entertainment, professionalism, real-time nature, and sociability confirm that consumers respond to a composite retail environment in which information quality, experiential stimulation, and social embeddedness coexist. This finding advances the literature by moving beyond narrowly specified feature studies and by showing that the live-streaming environment should be modeled as a bundle of differentiated but simultaneous stimuli. The evidence also justifies the S–O–R framing: purchase intention is neither a purely rational calculation nor a purely affective reaction, but the outcome of exposure to multiple features that jointly shape consumer judgement.

Professionalism emerged as the strongest direct predictor of purchase intention, and this result deserves emphasis. In markets where consumers face persistent uncertainty over authenticity, quality, and suitability, expertise becomes a scarce and persuasive resource. A live-streaming host who explains product functions clearly, addresses questions concretely, and conveys evidence-based confidence does more than perform competence; such a host reduces decision risk. The result is consistent with the source credibility logic underpinning Ohanian's framework and with live-streaming

Table 17 | Moderating effect results

Path	β	t	p	2.5%	97.5%
CPV → Purchase intention	0.223	4.577	0.000	0.127	0.316
Anticipated regret × CPV → Purchase intention	-0.140	3.785	0.000	-0.213	-0.070

Table 18 | Conditional effects at different levels of anticipated regret

Hypothesis	Path	β	t	p	2.5%	97.5%	Result
	CPV → CPI (Mean AR)	0.230	4.378	0.000	0.129	0.335	—
H3a	CPV → CPI (High AR: +1 SD)	0.082	1.336	0.182	-0.035	0.202	Not supported
H3b	CPV → CPI (Low AR: -1 SD)	0.379	5.459	0.000	0.241	0.512	Supported

Table 19 | Summary of hypothesis testing

Hypothesis	Result
H1a: Interactivity significantly and positively affects purchase intention.	Supported
H1b: Visualization significantly and positively affects purchase intention.	Supported
H1c: Entertainment significantly and positively affects purchase intention.	Supported
H1d: Professionalism significantly and positively affects purchase intention.	Supported
H1e: Real-time significantly and positively affects purchase intention.	Supported
H1f: Sociability significantly and positively affects purchase intention.	Supported
H2a: CPV mediates the interactivity–purchase intention relationship.	Supported
H2b: CPV mediates the visualization–purchase intention relationship.	Supported
H2c: CPV mediates the entertainment–purchase intention relationship.	Supported
H2d: CPV mediates the professionalism–purchase intention relationship.	Supported
H2e: CPV mediates the real-time–purchase intention relationship.	Supported
H2f: CPV mediates the sociability–purchase intention relationship.	Supported
H3a: High anticipated regret negatively moderates the CPV–purchase intention relationship.	Not supported
H3b: Low anticipated regret positively moderates the CPV–purchase intention relationship.	Supported

research showing that consumers translate expertise into trust and trust into behavioral readiness. In the Guangdong context, the priority consumers place on professionalism likely reflects a wider market reality in which enthusiasm alone is insufficient to overcome doubt. The compressed article therefore preserves a key message from the thesis: professional credibility is not an optional embellishment but a central conversion driver.

Interactivity and visualization also matter strongly, though for somewhat different reasons. Interactivity gives consumers access to responsive clarification, which reduces ambiguity and personalizes the decision process. Visualization makes the product legible. Together they reproduce, in digital form, two things that physical retail traditionally offered: the chance to inspect the product and the chance to ask someone knowledgeable about it. The fact that these features remain highly significant even when professionalism, entertainment, and sociability are modeled simultaneously suggests that consumers do not experience them as redundant. Rather, they appear to fulfill distinct evaluative needs within the same session. Guangdong consumers seem to want live-streaming rooms that are credible, responsive, and visually informative at once.

The mediation results show that customer perceived value is the central psychological bridge linking feature perceptions to behavioral intention. This matters theoretically because it shifts the explanation away from feature fetishism. Interactivity is not important because it is technologically impressive in itself; it is important because it makes the shopping encounter feel more worthwhile. Visualization matters because it improves the perceived trade-off between benefits and uncertainty. Sociability matters because it changes the social returns of participation. Entertainment matters because it adds emotional worth to the session. By demonstrating partial mediation across all six features, the study confirms that customer perceived value is a robust integrative construct for live-streaming commerce. At the same time, the persistence of significant direct paths reminds us that value is not the whole story. Future work can build on this by modeling trust, para-social interaction, flow, or affective arousal as parallel pathways.

One of the article's most important theoretical contributions lies in the moderation results. The original thesis hypothesized distinct upward and downward regret dynamics, but the empirical pattern is more revealing than a simple split confirmation would have been. High anticipated regret does not merely attenuate the value–intention link; it renders that link non-significant. This suggests that anticipated regret may function as a threshold-like decision breaker in live-streaming settings. Once consumers become sufficiently worried about future disappointment, better alternatives, or the consequences of a rushed decision, value-based reasoning loses its behavioral force. In other words, favorable value perceptions remain cognitively present, but they stop con-

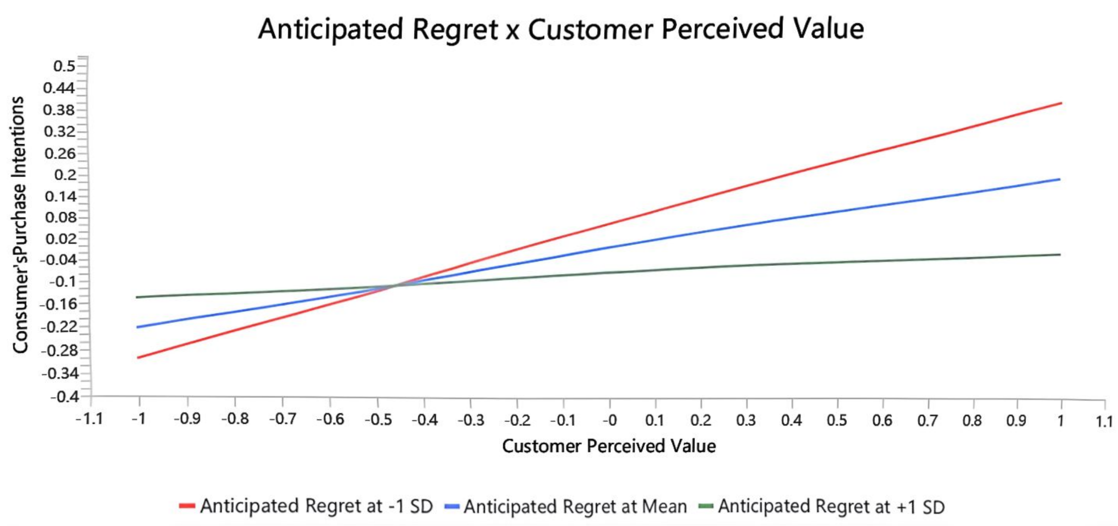

Figure 5 | Simple slope analysis of the moderating effect of anticipated regret on the customer perceived value–purchase intention relationship

verting into action. That pattern refines classical regret theory for fast, socially visible digital marketplaces and helps explain why high feature evaluations do not always yield high conversion rates.

The Guangdong context sharpens the relevance of this threshold effect. In a collectivist and socially dense market, live-streaming shopping is rarely an isolated act. Viewers observe others' comments, gauge crowd momentum, compare social cues, and often encounter urgency-laden prompts that compress reflection time. Under these conditions, anticipated regret is likely to become a more general emotional response to uncertainty than a cleanly separable pair of upward and downward states. The study's results are compatible with that interpretation. Low anticipated regret strengthens the value–intention relationship, but high anticipated regret does not simply reverse the relationship; it neutralizes it. The implication is that the functional form of regret in live-streaming contexts may be nonlinear and context dependent. This is one reason the article contributes not only to live-streaming research but also to the internationalization of consumer-behavior theory.

Taken together, the findings answer the three research questions in a coherent way. First, all six live-streaming features significantly affect purchase intention. Second, customer perceived value partially mediates those effects. Third, anticipated regret significantly moderates the conversion of perceived value into behavioral intention, with low regret strengthening the relationship and high regret effectively breaking it. The model therefore explains both how live-streaming features generate purchase intention and why that process can fail even when consumers recognize value. This dual explanation is precisely what a compressed journal version must preserve from the full thesis, because it captures the study's distinctive analytical contribution.

The result for sociability is especially important for understanding live-streaming commerce in collectivist settings. The feature's significant direct effect, coupled with its meaningful indirect effect through perceived value, indicates that social interaction is not merely decorative. Viewers appear to treat peer exchange and communal atmosphere as part of the utility of the shopping experience itself. In other words, sociability is not just a route to awareness; it is part of the value proposition. This helps explain why live-streaming commerce can outperform otherwise comparable static product pages even when both offer similar prices and product information.

Entertainment should likewise not be dismissed because it produced the smallest direct coefficient. Its significance demonstrates that consumers continue to value the experiential side of live-streaming commerce, even in a market that seems to weight credibility heavily. The implication is that platform effectiveness depends on disciplined hybridity: sessions must remain enjoyable enough to sustain attention without allowing entertainment to crowd out information, credibility, or transparency. This balance is one reason live-streaming commerce remains difficult to standardize successfully across merchants and product categories.

The mediation results also speak to a broader theoretical issue in digital retail research: whether technological affordances influence behavior directly or through meaning-making processes. The present study supports the latter view. Live-streaming features matter because consumers interpret them as altering the worth of the shopping encounter. That perspective strengthens process-based theories of digital commerce by showing that a stimulus-oriented explanation is incomplete unless it also specifies the internal evaluative mechanism through which stimuli become behaviorally relevant. Customer perceived value performs that role convincingly in the current model.

From a methodological perspective, the combination of balanced direct effects, pervasive partial mediation, and conditional moderation produces a richer picture than any single modeling step would have allowed. A direct-effects model alone would have shown that features matter, but it would not have explained why. A mediation model alone would have shown the importance of value, but not why value sometimes fails to produce intention. A moderation model without the feature structure would have shown emotional contingency, but not what generates the underlying evaluations. The integrated design is therefore not simply more comprehensive; it is necessary for capturing the layered logic of live-streaming purchase decision-making.

These points clarify why the article's contribution exceeds a regional case study. Guangdong is the empirical setting, but the analytical lesson travels more widely. In digital shopping environments where products are presented socially, persuasion unfolds synchronously, and choice is compressed into narrow time windows, purchase intention depends on both the creation of positive value and the management of anticipated negative emotion. That lesson is relevant to emerging live commerce markets beyond Guangdong and to platform forms that increasingly blend sociality, entertainment, and retail into a single stream-based interface.

Implications

The theoretical implications are threefold. First, the study extends feature-based research by demonstrating that live-streaming commerce should be treated as a multidimensional stimulus environment. Second, it places customer perceived value at the centre of explanation, thereby integrating functional, emotional, and social evaluations into the S–O–R architecture. Third, it refines regret-based decision logic by showing that anticipated regret in live-streaming commerce may operate as a threshold-like inhibitor rather than a weak, continuous dampener. These implications matter because they push the literature beyond descriptive lists of platform attributes and toward a more process-oriented understanding of how digital retail encounters generate or suppress behavioral intention.

The managerial implications are immediate. Merchants and platforms seeking higher conversion rates should prioritize professionalism before spectacle. Investment in host training, product knowledge, evidence-based explanation, and disciplined Q&A is likely to yield stronger returns than relying mainly on excitement or urgency. Interactivity and visualization should be designed as information-quality tools rather than merely attention devices. Consumers need clear demonstrations, rapid clarification, and a sense that the host can respond to case-specific concerns. Sociability should also be cultivated deliberately, because peer exchange and visible participation enrich value perception, especially in collectivist markets where purchasing is socially interpreted rather than strictly individual.

The moderation findings add an important caution. Many live-streaming strategies depend on time pressure, flash sales, and scarcity cues. The present results suggest that such tactics can backfire when they intensify anticipated regret beyond a manageable level. Rather than simply adding urgency, practitioners should balance urgency with reassurance. Clear return policies, truthful disclosure of limitations, transparent comparison claims, post-purchase service guarantees, and moderated promotional tone may help maintain the behavioral influence of perceived value. In other words, value enhancement and regret reduction should be treated as complementary conversion strategies rather than separate managerial agendas.

The policy implications are equally relevant. If high anticipated regret weakens consumers' ability to act on informed value judgements, then platform governance and consumer protection mechanisms become more than compliance matters; they become part of market efficiency. Policymakers and platform regulators should consider clearer disclosure rules for sponsorship, host claims, product limitations, and after-sales procedures. Strengthening complaint handling, return rights, and authenticity enforcement may reduce the emotional uncertainty that suppresses well-grounded purchase decisions. In a sector where commercial volume continues to rise rapidly, the stability of consumer trust is likely to depend not only on innovation but also on the visibility of protection mechanisms.

For host management, the findings suggest a training agenda that is simultaneously cognitive and emotional. Hosts need the product knowledge to explain, compare, and defend recommendations, but they also need the situational judgement to recognize when persuasive pressure may be tipping into regret induction. Strong hosts are not simply energetic; they are strategically credible. They know when to intensify interaction, when to visualize product details, and when to slow the pace of persuasion so that consumers remain confident in the decision they are about to make.

For platform design, the study implies that interface features should support evaluation rather than merely speed. Responsive comment display, pinned clarifications, visual zoom functions, standardized product information panels, and visible after-sales policy cues can all reinforce perceived value while lowering the emotional uncertainty that feeds anticipated regret. Platforms often treat trust and convenience as back-end service issues, but the present results suggest that these elements are experienced directly within the live-streaming room and should therefore be designed into the front-end consumer journey.

Conclusion, Limitations, and Future Research

This article has compressed the original doctoral thesis into a journal-oriented format while preserving its core theoretical structure, empirical evidence, and figure-table logic. Using data from 498 consumers in Guangdong Province, it shows that live-streaming shopping features shape purchase intention both directly and indirectly. Professionalism, interactivity, and visualization are particularly influential, while customer perceived value serves as a consistent partial mediator across all six feature pathways. Anticipated regret emerges as a powerful emotional boundary condition: low regret allows perceived value to convert into intention strongly, whereas high regret weakens that conversion to the point of non-significance.

The study is not without limitations. Its cross-sectional design constrains strong causal inference, its empirical scope is confined to one province, and its survey-based measures cannot fully reproduce the rapidly shifting situational cues of actual live-streaming sessions. Future work should therefore examine other regional and product contexts, adopt longitudinal or experimental designs, and model additional mediators and moderators such as trust, flow, social presence, or risk aversion. Even so, the present article offers a clear and empirically grounded conclusion: live-streaming commerce succeeds when platforms generate value and simultaneously keep regret at bay. That combination, rather than visibility or traffic alone, is what ultimately turns engagement into purchase intention.

Future research should make fuller use of causal and comparative designs. Experimental studies could manipulate professionalism, urgency cues, or social visibility directly in simulated live-streaming environments to determine whether the threshold pattern observed for anticipated regret is stable across product categories. Longitudinal designs could also examine whether repeated exposure changes the feature hierarchy itself—for example, whether experienced viewers become less susceptible to entertainment and more dependent on professionalism or whether trust accumulated over time reduces the disruptive effect of regret. Such work would deepen the theoretical trajectory opened by the present article while preserving its central insight that value creation and regret management are inseparable in live-streaming commerce.

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