Informational and Affective Interactions in Live-Streaming Commerce: User Engagement and Its Relationship with Trust-Related Expressions Based on Multiple Public Data So

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Abstract

Live-streaming commerce has emerged as an important format of online shopping, integrating product demonstrations, real-time communication, entertainment, and transactional functions. Streamers not only provide product-related information but also engage viewers through emotional expression, interpersonal communication, and relationship-building strategies. Although informational and affective interactions may influence consumer responses through different mechanisms, user engagement, streamer trust, and purchase intention represent distinct constructs that should not be treated as interchangeable.

This study aims to examine the characteristics of informational and affective interactions in live-streaming commerce, investigate their relationships with observable user engagement and trust-related expressions, and explore the potential association between trust-related expressions and purchase-intention expressions. A multiple-source public data analysis approach is proposed, combining literature-based evidence synthesis, public-text coding, thematic analysis, descriptive statistics, and appropriate statistical modelling. The planned data sources include publicly accessible livestream content, user comments, industry reports, and published academic research. Artificial intelligence (AI) will be used to assist with literature retrieval, text classification, and data organization, while the researcher will be responsible for source verification, coding decisions, and validation of analytical results.

Existing research provides an initial empirical foundation. Luo, Xu, and Zheng (2024) analysed real-world data from the Dongfang Zhenxuan livestreaming channel on Douyin, distinguishing

informational and affective topics and examining their relationships with different dimensions of user engagement. Tian et al. (2023) investigated the antecedents of streamer trust and its relationship with consumer purchasing behavior using a cognition–affect–conation framework. Liu and Zhang (2024) examined the relationships among interactive elements, social presence, trust, and purchase intention using questionnaire data from 326 live-streaming commerce consumers. These studies provide relevant evidence for examining interaction types, user engagement, and trust-related variables. However, their findings cannot substitute for the original cross-platform comment data that this study intends to collect.

This study conceptualizes trust-related expressions in public comments as observable textual indicators rather than direct measures of consumers' underlying psychological trust. Similarly, purchase-intention expressions are distinguished from actual purchasing behavior. The proposed research is expected to establish a reproducible framework for classifying livestream interactions and to provide a more nuanced understanding of the relationships among information provision, affective engagement, and consumer responses. As the collection of original cross-platform data has not yet been completed, this paper does not report uncalculated sample sizes, statistical coefficients, or significance tests as empirical findings.

Keywords: live-streaming commerce; informational interactions; affective interactions; user engagement; streamer trust; public data analysis

1. Introduction

1.1 Research Background

Live-streaming commerce integrates product demonstrations, real-time communication, entertainment, and transaction-related functions within a single digital environment. Unlike conventional e-commerce, which relies primarily on product images, written descriptions, and consumer reviews, live-streaming commerce enables streamers to demonstrate products, respond to questions, explain product features, and establish interpersonal connections with viewers through verbal and non-verbal communication.

Within this environment, streamer communication serves multiple purposes. On the one hand, streamers provide information about product specifications, prices, performance, usage

scenarios, and purchasing options, helping consumers reduce information-search costs. On the other hand, they use storytelling, humor, emotional expression, and relational language to create a sense of intimacy, sustain attention, and encourage interaction. These two broad communication functions can be conceptualized as informational and affective interactions.

However, information provision and affective engagement do not necessarily produce identical consumer responses. Detailed product explanations may help consumers understand a product without immediately generating more comments or gifts. Affective communication may increase user engagement without necessarily demonstrating that consumers have developed greater trust in the streamer or a stronger intention to purchase. Research on livestream interactions should therefore distinguish observable engagement behaviors, publicly expressed trust judgements, and purchase intention as separate outcome variables.

Luo et al. (2024) analyzed data from the Dongfang Zhenxuan livestreaming channel on Douyin, using text-mining techniques to identify informational and affective topics and investigate their relationships with different dimensions of user engagement. Their findings suggest that streamer discourse can provide a meaningful basis for examining how livestream content relates to user responses.

Meanwhile, Tian et al. (2023) investigated the antecedents of streamer trust and its relationship with consumer purchasing behavior. Liu and Zhang (2024) examined interactions, social presence, trust, and purchase intention using questionnaire data from live-streaming commerce consumers. These studies provide relevant theoretical and empirical foundations, although their data sources and measurement approaches differ.

1.2 Research Questions

Against this background, the study addresses the following research questions:

- **RQ1**: What are the main characteristics of informational and affective interactions in live-streaming commerce?
- **RQ2**: How are informational and affective interactions associated with observable user engagement behaviors?
- **RQ3**: How are these two interaction types associated with trust-related expressions in

public user comments?

- **RQ4**: Is there an association between trust-related expressions and purchase-intention expressions?
- **RQ5**: Are streamer expertise cues associated with differences in trust-related expressions across interaction types?

RQ5 is exploratory. Whether it can be examined statistically will depend on the availability, quality, and comparability of data relating to streamer expertise cues, interaction types, and trust-related expressions.

1.3 Research Significance

This study has three potential contributions.

First, from a theoretical perspective, it distinguishes streamer discourse, user engagement, trust-related expressions, and purchase-intention expressions. This approach avoids reducing different consumer responses to a single measure of interaction effectiveness.

Second, from a methodological perspective, the study explores how publicly available livestream content, user comments, industry materials, and academic research can be integrated into a transparent analytical framework. Explicit coding rules and validation procedures are intended to improve the reproducibility of the research process.

Third, from a practical perspective, the findings may help live-streaming commerce practitioners understand how informational and affective communication correspond to different user responses. Such insights could inform livestream content design and interaction strategies. However, practical recommendations should be based on the results of the actual data analysis rather than inferred solely from comment volume or previous studies.

2. Literature Review and Analytical Framework

2.1 Informational and Affective Interactions in Live-Streaming Commerce

Streamer communication in live-streaming commerce serves both informational and relational functions. To investigate the relationships between different types of communication and user

responses, it is necessary to establish clear classification criteria.

Informational interactions primarily concern product knowledge and problem-solving. Examples include explanations of product specifications, materials, functions, prices, usage instructions, product comparisons, and responses to product-related questions. Their defining characteristic is the provision of information that may assist consumers in making purchasing decisions and reducing uncertainty.

Affective interactions primarily involve emotional expression and relational communication. Examples include personal stories, humour, emotional responses, expressions of appreciation, and language intended to create a sense of closeness. Such interactions may strengthen viewers' familiarity with the streamer and their sense of social presence. Their effects, however, may depend on product category, consumer preferences, and the livestreaming context.

Luo et al. (2024) directly classified streamer topics as informational or affective and examined their relationships with behavioral, emotional, and relational engagement. Their findings indicated that informational topics were negatively associated with certain behavioural engagement measures, including commenting and gifting, and with emotional and relational engagement. Affective topics were positively associated with several user engagement measures.

These findings do not imply that informational interactions lack value. Commenting and gifting represent specific forms of engagement and do not fully capture whether viewers understand a product, trust the streamer, or complete a purchase. Informational interactions may help reduce uncertainty without necessarily producing higher values across every engagement indicator. Accordingly, this study does not assume that either interaction type will outperform the other across all outcome variables.

2.2 The Formation and Role of Streamer Trust

Trust is an important construct in situations where consumers must make judgements under conditions of incomplete information and uncertainty. In live-streaming commerce, consumers may evaluate not only the reliability of a product but also the streamer's knowledge, honesty, and ability to provide useful recommendations.

Tian et al. (2023) examined the antecedents of streamer trust and its relationship with consumer purchasing behavior using a cognition–affect–conation framework. Their study provides direct empirical evidence relevant to understanding streamer trust in live-streaming commerce. Liu and Zhang (2024) collected questionnaire data from 326 live-streaming commerce consumers and used structural equation modelling to examine interactions between consumers and streamers, interactions among consumers, social presence, trust, and purchase intention. Their findings indicated positive relationships between certain forms of interaction and purchase intention, with social presence and trust mediating some of these relationships.

Nevertheless, psychological trust measured through established questionnaire scales differs from trust-related expressions observable in public comments. Some consumers may trust a streamer without commenting, while others may mention a streamer because of controversy, criticism, or sarcasm. Public comments therefore provide only a partial representation of consumer perceptions.

For this reason, the present study uses the term trust-related expressions to describe observable textual indicators rather than treating them as direct measures of consumers' underlying psychological trust.

2.3 User Engagement and Purchase Intention

User engagement is a commonly examined outcome in live-streaming commerce research. It may include commenting, liking, sharing, gifting, emotional engagement, and relational engagement. These indicators reflect different dimensions of user response and should not be combined into a single measure without a clear conceptual and methodological justification.

Purchase intention refers to a consumer's subjective inclination to buy a product and is distinct from completed purchasing behaviour. Public comments such as requests for prices, questions about discounts, expressions of interest in buying, and reports of completed purchases represent different types of information. They should not be classified as a single undifferentiated purchase-intention indicator.

Liu and Zhang (2024) found that different interactive elements were associated with purchase

intention and that social presence and trust helped explain some of these relationships. However, their findings were derived from questionnaire data and structural equation modelling. They cannot be directly translated into rates of purchase-intention expressions in public comments, nor do they establish that the same relationships necessarily occur across different platforms.

Accordingly, this study treats user engagement, trust-related expressions, and purchase-intention expressions as separate analytical outcomes. Their relationships will be examined only where the collected data support meaningful comparisons.

2.4 Theoretical Foundations

This study primarily draws on the Stimulus–Organism–Response (S-O-R) framework. The environmental psychology framework developed by Mehrabian and Russell (1974) proposes that environmental stimuli may influence behavioural responses through individuals' internal states. The framework has subsequently been applied to the study of consumer responses to shopping environments and informational cues.

In the present study, informational and affective streamer communication can be conceptualised as external stimuli. Trust-related judgements and emotional responses represent constructs associated with consumers' internal states, while observable comments, engagement behaviours, and purchase-intention expressions represent potential responses.

However, because this study analyses public texts rather than directly measuring consumers' psychological states through validated scales, the S-O-R framework primarily serves as a theoretical organising structure. It should not be interpreted as a fully validated causal model within the present research.

Source credibility theory also provides a relevant foundation. Hovland, Janis, and Kelley (1953) examined the relationship between source characteristics and persuasive communication. A streamer's expertise cues may influence how viewers interpret product recommendations. Nevertheless, the use of technical terminology does not necessarily establish actual expertise, and a comment describing a streamer as knowledgeable represents a consumer evaluation rather than an objective assessment of competence.

This study therefore distinguishes observable expertise cues in livestream content from

viewers' expressed evaluations of streamer expertise.

2.5 Literature Synthesis and Research Questions

Existing studies have investigated streamer discourse, user engagement, streamer trust, and purchase intention from different perspectives. However, they differ in data sources, research designs, and measurement approaches.

Research area	Existing evidence	Approach adopted in this study
Informational and affective discourse	Research using real-world livestream data	Classify interaction content using explicit coding rules
Interaction and user engagement	Existing livestream data and survey research	Analyse publicly available engagement indicators
Streamer trust	Existing questionnaire-based studies	Examine trust-related expressions in public comments
Purchase intention	Existing questionnaire-based studies	Analyse purchase-intention expressions as a separate textual indicator
Streamer expertise	Previous research on source credibility and expertise	Treat expertise as an exploratory variable, subject to data quality

The objective is not simply to demonstrate that interaction matters. Rather, this study seeks to investigate how different types of interaction are represented in public livestream content and whether they are associated with distinct patterns of user response.

A definitive claim that these relationships constitute a novel research gap would be premature

without a more systematic search and comparison of the existing literature.

3. Research Methodology

3.1 Research Design

This study adopts a multiple-source public data analysis design, combining literature-based evidence synthesis, textual content analysis, descriptive statistics, and appropriate statistical modelling.

No formal questionnaire survey or experiment is conducted as part of the proposed research. The planned data sources include publicly accessible livestream content, user comments, industry reports, and published academic studies. AI will assist with literature retrieval, text classification, deduplication, thematic analysis, and data organization. The researcher will verify sources, establish coding rules, and validate the analytical results.

The research involves two analytical stages.

The first stage synthesizes published literature and publicly available research materials to define the variables, establish the analytical framework, and formulate research questions.

The second stage analyses original public online texts after they have been collected and verified. This stage examines the relationships between interaction types and observable user responses.

The samples and statistical findings reported in published papers will not be merged with the original comment dataset. Such integration would require a separate systematic review or meta-analytic design using comparable effect sizes and appropriate methods.

3.2 Data Sources and Search Strategy

Four categories of data are proposed.

First, publicly accessible livestream content. The study will consider livestream recordings, clips, public videos, and associated interaction information available on platforms such as Douyin, Taobao Live, and Kuaishou. Only content that can actually be accessed in accordance with applicable platform rules will be included in the final dataset.

Second, public user comments. Comments directly associated with selected livestream content will be collected to examine expressions concerning products, streamers, interaction styles, trust, and purchasing behavior. Comments with insufficient context, suspected duplication, or ambiguous meanings will be flagged as uncertain or excluded rather than forced into a predefined category.

Third, public industry reports and statistical materials. These sources will be used to establish the industry context and describe the broader platform environment. For each report, the publishing organization, publication date, population or market coverage, and indicator definitions will be recorded. Statistics with incompatible definitions will not be compared directly.

Fourth, academic literature. Priority will be given to empirical studies directly addressing live-streaming commerce, interaction types, streamer trust, user engagement, and purchase intention. Relevant foundational theories will also be consulted. The literature screening process should record search dates, databases or websites, search terms, and inclusion and exclusion criteria.

The key studies verified for this draft include Luo et al. (2024), Tian et al. (2023), and Liu and Zhang (2024). These studies provide an initial basis for the analytical framework but do not constitute an exhaustive systematic literature review.

3.3 Data Collection Period, Units of Analysis, and Inclusion Criteria

The literature verification date for this draft is 1 October 2026. The collection of original cross-platform online data has not yet been completed. Therefore, this date must not be presented as the actual collection date of the public comment dataset.

During formal data collection, the start and end dates for each platform will be recorded. Each observation should retain its source URL, publication date or verifiable content timestamp, collection date, content type, and inclusion status.

A stratified sampling approach is proposed:

- Platform will serve as the first sampling stratum.
- Product category or livestream topic will serve as the second stratum.

- Individual livestream sessions or public videos will serve as the third stratum.
- Livestream segments, streamer utterances, or individual user comments will serve as the specific units of analysis.

Different research questions require different units of analysis. For example, a semantically complete streamer utterance may serve as the unit for classifying interaction types, whereas an individual comment or a clearly defined collection of comments may serve as the unit for analyzing trust-related expressions.

Inclusion criteria will require that content be directly relevant to live-streaming commerce, traceable to a verifiable source, and sufficiently contextualized for analysis. Exclusion criteria will include unverifiable reposts, obvious duplicates, irrelevant comments, and texts that cannot be reliably classified because of missing context.

The final sample size must be determined from the actual collection and cleaning process. The completed study should report the number of original content items, cleaned content items, original comments, deduplicated comments, excluded records, and valid observations, together with the sample distribution across platforms.

3.4 Operational Definitions and Coding Scheme

To improve analytical reproducibility, the following operational definitions are proposed.

Variable	Operational definition	Potential indicators
Informational interactions	Communication providing product facts, specifications, usage instructions, comparisons, or answers to questions	Frequency and proportion of informational utterances
Affective interactions	Communication involving storytelling, humor, emotional expression, or relational language	Frequency and proportion of affective utterances

Mixed interactions	Utterances containing both substantive information and affective elements	Frequency and proportion of mixed utterances
User engagement	Observable user responses to livestream content	Comments, likes, shares, and other available indicators
Trust-related expressions	Explicit evaluations of streamer reliability, honesty, expertise, or recommendation credibility	Number and proportion of relevant comments
Expertise cues	Observable references to product knowledge, explanatory competence, or professional credentials	Frequency or coded level of expertise cues
Purchase-intention expressions	Explicit expressions of purchase interest, hesitation, or enquiries about purchasing conditions	Number and proportion of comments in each category
Purchase feedback	Statements explicitly reporting a purchase or product use	Number and proportion of purchase-feedback comments

Informational and affective elements may coexist within the same utterance. Before the formal analysis, the researcher must decide whether to use multilabel classification or assign each utterance a dominant category. If dominant-category coding is adopted, explicit decision rules should be established, and ambiguous cases should be documented.

Trust-related expressions should be classified into at least four categories: positive trust, negative trust, skepticism, and indeterminate expressions. This prevents all mentions of a streamer from being incorrectly treated as evidence of trust.

Purchase-related comments should similarly be differentiated into purchase intention, self-

reported purchasing experience, purchase-related enquiries, and expressions without a clear purchase orientation.

3.5 AI-Assisted Text Analysis and Quality Control

AI may assist with preliminary classification and thematic analysis, but its outputs must be treated as coding results requiring verification rather than as inherently reliable facts.

The proposed procedure is as follows:

1. Develop a manual coding guide that defines each category, its boundaries, and representative examples.

2. Select a subset of the collected texts and have two coders independently classify them.

3. Compare the independent coding results and calculate Cohen's kappa or another appropriate inter-coder agreement statistic.

4. Discuss disagreements, revise the coding rules where necessary, and retain records of these revisions.

5. Use AI-assisted classification for the remaining texts, followed by manual verification of a sample.

6. Report unclassifiable texts, ambiguous contexts, and classification errors rather than concealing uncertainty.

7. If two independent human coders are unavailable, this limitation should be stated explicitly. A manually reviewed sample should then be used to evaluate the accuracy or consistency of the AI-assisted classifications.

Unvalidated AI classifications must not be described as highly reliable coding results.

3.6 Statistical Analysis

Descriptive statistics will first be used to report the distribution of observations across platforms, product categories, and interaction types. Frequencies and proportions will be calculated for the relevant text categories.

Next, the relationships between interaction types and user engagement indicators will be

examined. For count outcomes, such as comment or like counts, Poisson regression or negative binomial regression may be considered depending on the distribution and degree of overdispersion. For continuous outcomes that satisfy the relevant assumptions, an appropriate linear model may be used.

For trust-related expressions and purchase-intention expressions, logistic regression or contingency-table analysis may be employed when the sample size and category distributions support such analyses. Depending on the research question, models may control for relevant observable factors, including platform, product category, livestream content, collection period, and streamer characteristics.

Testing whether streamer expertise cues moderate the relationship between interaction type and trust-related expressions requires sufficient data in which expertise cues, interaction types, and trust-related expressions can be matched within a clearly defined unit of analysis. The sample must also be adequate for estimating interaction terms. If these conditions are not met, expertise should remain an exploratory qualitative variable rather than being subjected to an unreliable statistical test.

Robustness checks will include alternative interaction-coding rules, platform-specific estimates, exclusion of uncertain texts, and assessments of the influence of duplicated content.

All statistical coefficients, significance levels, and confidence intervals must be calculated from the actual dataset. They will not be generated in advance or presented without empirical verification.

3.7 Research Ethics and Reproducibility

The study will use only publicly accessible materials obtained in accordance with applicable platform rules and relevant legal and ethical requirements. It will not attempt to bypass access controls or collect personal sensitive information unrelated to the research objectives.

When reporting user comments, aggregated results or appropriately processed examples will be preferred. Reproducing searchable verbatim comments will be avoided when doing so could unnecessarily expose ordinary users.

Source records, data dictionaries, coding manuals, and analytical procedures will be retained to support reproducibility.

The researcher will disclose the specific roles of AI in retrieval, classification, and analysis and will remain responsible for verifying all sources, coding decisions, statistical results, and conclusions.

4. Research Results

4.1 Overview of the Verified Literature

As of 1 October 2026, three empirical studies directly relevant to the central research topic have been verified for this draft. They employ livestream platform data or consumer surveys to investigate streamer discourse, user engagement, trust, and purchase intention from different perspectives.

Study	Data and method	Relevance to the present study
Luo, Xu, and Zheng (2024)	Dongfang Zhenxuan livestream data and text mining	Provides a direct basis for classifying informational and affective topics and analyzing user engagement
Tian et al. (2023)	Questionnaire-based research on streamer trust	Provides theoretical and empirical reference for the antecedents of streamer trust and its relationship with purchasing behavior
Liu and Zhang (2024)	Questionnaire data from 326 live-streaming commerce consumers and structural equation modelling	Provides evidence concerning interactions, social presence, trust, and purchase intention

Sources: Luo et al. (2024); Tian et al. (2023); Liu and Zhang (2024).

The sample of 326 respondents reported in Table 1 belongs to the original study by Liu and Zhang (2024). It is not the number of comments collected for the present research. The samples from these three studies cannot be directly combined, nor can their sample sizes be used to calculate the overall sample size of this study's cross-platform dataset.

4.2 Existing Evidence on Informational and Affective Interactions

Luo et al. (2024) used real-world data from the Dongfang Zhenxuan livestreaming channel to distinguish informational and affective topics through text mining. They examined relationships with behavioral, emotional, and relational engagement.

Their findings indicated that informational topics were negatively associated with certain behavioral engagement indicators, including commenting and gifting, and with emotional and relational engagement. Affective topics were positively associated with commenting, gifting, and several other user engagement indicators. The study also reported no statistically significant relationship between informational topics and liking behavior.

These findings suggest that different types of streamer discourse may correspond to different patterns of user engagement. However, the results are specific to the original study's data, variable definitions, and analytical conditions. They cannot establish that identical relationships occur across all platforms, product categories, or livestreaming contexts.

For the present study, the existing evidence supports coding informational and affective interactions separately and treating user engagement as a multidimensional outcome rather than a single measure of interaction effectiveness.

4.3 Existing Evidence on Streamer Trust and Purchase Intention

Tian et al. (2023) developed a research model based on the cognition–affect–conation framework to examine the antecedents of streamer trust and its relationship with consumer purchasing behavior. Their study provides relevant empirical evidence for understanding the role of streamer trust in live-streaming commerce.

Liu and Zhang (2024) collected questionnaire data from 326 live-streaming commerce consumers and analyzed the data using structural equation modelling. Their findings indicated positive relationships between certain forms of interaction and purchase intention. Social

presence mediated some of these relationships, while trust mediated the relationships between certain interactive elements and purchase intention. The study also reported that susceptibility to informational influence positively moderated the relationship between consumer–streamer interaction and purchase intention.

These findings provide evidence of potential relationships among interaction, trust, and purchase intention. However, because the study relied on questionnaire measures and structural equation modelling, its results cannot be directly converted into proportions of trust-related or purchase-intention expressions in public comments.

4.4 Synthesis of the Existing Evidence

Three cautious conclusions can be drawn from the existing literature.

First, streamer discourse can be classified into informational and affective categories, and the two types may be associated with different dimensions of user engagement.

Second, streamer trust is an important construct for understanding consumer responses in live-streaming commerce. Existing studies provide theoretical and empirical support for examining relationships among interaction, trust, and purchase intention.

Third, user engagement, trust, and purchase intention are distinct outcomes and should not be treated as interchangeable. A high volume of comments does not necessarily indicate high trust, and expressions of purchase interest do not establish that a transaction has occurred.

The original cross-platform comments have not yet been collected, cleaned, and statistically analyzed. Consequently, this study cannot currently report actual sample sizes by platform, proportions of interaction types, rates of trust-related expressions, rates of purchase-intention expressions, or regression coefficients. These results must be calculated after the original data have been obtained and verified. They cannot be inferred from published studies or generated by AI.

5. Discussion

5.1 Informational and Affective Interactions Require Different Evaluation Criteria

Existing literature suggests that informational and affective discourse may be associated with

different forms of user engagement. This indicates that livestream operators should not evaluate the effectiveness of a communication strategy solely through comment counts, likes, or gifts.

The potential value of informational interactions can be examined in terms of information completeness, problem-solving, product understanding, and uncertainty reduction. Affective interactions can be examined in terms of emotional engagement, relational expressions, and continuity of interaction. These two forms of communication may complement one another rather than function as simple substitutes.

These interpretations nevertheless require examination using the actual public data. For example, a livestream with relatively few comments may indicate that viewers are concentrating on a product demonstration, or it may reflect a lack of engaging content. Comment volume alone cannot distinguish between these explanations.

5.2 Limitations of Trust-Related Expressions as a Measure

Public comments provide observable material for examining how users express trust, but such expressions are not equivalent to psychological trust itself.

For example, the statement "This streamer explains the product professionally" may be coded as a positive evaluation of expertise. The statement "The streamer's claims are exaggerated" may indicate scepticism. By contrast, "The streamer is telling stories again" does not necessarily contain an explicit trust judgement.

If the coding rules are unclear, neutral references, sarcasm, and negative evaluations may be incorrectly classified as evidence of trust. This study should therefore distinguish positive trust expressions, negative trust expressions, expertise evaluations, and indeterminate expressions, and assess coding quality through manual verification.

The results should be reported as the proportion of trust-related expressions rather than as a direct measure of the trust levels of all livestream viewers.

5.3 Purchase-Intention Expressions Are Not Equivalent to Actual Purchases

Comments asking about prices, discounts, purchasing links, or product specifications may reflect purchase interest, but they may also represent information seeking. Statements such

as "I have ordered it" represent self-reported purchasing experiences, which remain distinct from transaction records verified by a platform.

The study should therefore distinguish purchase-related enquiries, expressions of purchase intention, reports of purchasing experiences, and verified transaction data. If verifiable transaction data are unavailable, the analysis should be limited to purchase-related expressions and should not be used to infer sales revenue or conversion rates.

5.4 Streamer Expertise as an Exploratory Variable

Expertise may influence how viewers interpret streamer communication and evaluate product recommendations. However, its measurement requires particular care.

If streamer expertise is inferred solely from the use of technical terminology, actual knowledge may be confused with communication style. If expertise is inferred from user comments, the resulting measure represents viewers' perceptions of expertise rather than the streamer's objective competence.

The study should therefore distinguish observable expertise cues in the content from user-expressed evaluations of expertise. Statistical analysis of the interaction between expertise cues and interaction type should be conducted only if both can be reliably measured and matched with trust-related expressions in a sufficiently large dataset.

5.5 Applicability of the Research Framework

The S-O-R framework provides a useful structure for organising the theoretical relationships among interaction stimuli, trust-related judgements, and user responses. However, public-text research generally lacks random assignment, experimental control, and comprehensive measurement of individual psychological states.

Even if the eventual statistical analysis identifies significant associations, the findings should primarily be described in terms of relationships, associations, or observed differences rather than definitive causal effects.

If subsequent research seeks to establish causal mechanisms, experiments or questionnaire-based studies could be conducted following the public data analysis. The present study should retain its focus on secondary data analysis and avoid interpreting correlation as

causation.

6. Research Limitations

This study has several limitations.

First, the original data collection remains incomplete. The evidence currently verified consists primarily of published studies. Original public livestream content and cross-platform comment data have not yet been collected. Therefore, this draft cannot report independent cross-platform statistical findings or claim that the proposed hypotheses have been empirically validated.

Second, platform data availability varies. Differences in content visibility, comment accessibility, engagement indicators, and platform access rules may introduce selection bias. Publicly accessible content may not represent the full range of livestreaming activity on a given platform.

Third, textual coding involves subjectivity. The boundaries between informational, affective, and mixed interactions are not always clear. Sarcasm, irony, internet slang, and missing context may affect classification accuracy. AI-assisted classifications require manual verification and reporting of coding agreement.

Fourth, public expressions do not fully represent consumer psychology. Some users watch livestreams without commenting, while others comment for entertainment, controversy, or social reasons. Trust-related expressions cannot fully represent psychological trust, and purchase-intention expressions cannot fully represent purchase intention among all viewers.

Fifth, causal inference is limited. Even after controlling for observable factors, associations in public texts may be influenced by product category, streamer popularity, promotional offers, traffic allocation, and audience composition. Unless a research design capable of supporting causal inference is employed, definitive causal claims should be avoided.

Sixth, cross-platform comparability requires verification. Platforms may differ in audience composition, recommendation mechanisms, content formats, and engagement metrics. Where measurement definitions cannot be harmonised, platform-specific analyses should be conducted rather than combining all observations indiscriminately.

Seventh, AI-assisted analysis may contain errors. AI may misinterpret context, duplicate observations, or inaccurately summarise literature. Researchers must independently verify sources, coding decisions, statistical procedures and maintain traceable records.

7. New Knowledge Expected from This Study

Because the cross-platform analysis of original data has not yet been completed, this section describes the types of knowledge the study may generate, rather than presenting unverified findings as established contributions.

First, the study aims to develop a public-text coding framework that distinguishes informational, affective, and mixed interactions while separately classifying user engagement, trust-related expressions, and purchase-intention expressions. Such a framework may help prevent different consumer responses from being treated as interchangeable.

Second, the study seeks to connect streamer discourse with specific forms of user expression in public comments. This may provide a more detailed understanding of how different interaction types correspond to observable response patterns, compared with studies that focus exclusively on a single purchase-intention outcome.

Third, the study explores how livestream content, user comments, industry materials, and published academic research can be integrated into a reproducible analytical process. Source documentation, coding manuals, and manual verification are intended to improve transparency and replicability. Fourth, the findings may inform subsequent questionnaire-based or experimental research by refining variable definitions and research hypotheses. For example, if the public-text analysis identifies a stable association between certain expertise cues and trust-related expressions, subsequent studies could investigate whether these cues influence psychological trust and purchase intention.

Whether these contributions constitute substantive academic innovation must be assessed after the systematic literature review and original data analysis have been completed. At this stage, it would be premature to claim that the study is the first to identify a particular relationship or that it has already established the superior effectiveness of one interaction type.

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