OPTIMIZING LIVESTREAMING SALES: CONFIGURATIONAL EFFECTS OF TIME ALLOCATION ACROSS SELLING STEPS ON PRODUCT PERFORMANCE

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ABSTRACT

Livestreaming commerce has become a key sales channel, yet streamer communication effectiveness, particularly their spoken content volume across selling steps, remains underexplored. Drawing on social exchange and complexity theory, we argue that multiple interdependent configurations of selling steps can lead to high product sales, consistent with the principle of equifinality. Focusing on snack products, this research examines how content volume allocation across four selling steps—approach, presentation, overcoming objections, and close sales—impacts product sales. Using fuzzy-set qualitative comparative analysis on data from a major snack brand’s livestreams, we identify three configurations associated with high product sales: (1) high content in approach, presentation, and close sales, with low overcoming objections; (2) high content in approach, overcoming objections, and close sales, with low presentation; and (3) high presentation with low approach and close sales (with overcoming objections as peripheral). Conversely, misalignment between approach and close sales, despite high presentation, is linked to low sales. These findings underscore the configurational nature of effective selling: multiple combinations of content volume across the four steps can drive high product sales. Further, the findings reveal that presentation and overcoming objections can substitute for each other, while approach and close sales are complementary. This research advances understanding of streamer communication effectiveness and provides actionable guidance for streamers on structuring scripts to improve sales.

Keywords: Livestreaming commerce; Salesperson communication effectiveness; Selling process; Topic modeling; fsQCA

1. Introduction

The emergence of digital technologies has profoundly transformed the traditional marketing landscape, shifting interactions from offline face-to-face encounters to online screen-to-screen engagements (Bharadwaj & Shipley, 2020; Yadav & Pavlou, 2014), especially in the aftermath of the COVID-19 pandemic (Rangarajan et al., 2021). Among various digital sales platforms, livestreaming commerce has emerged as a prominent one-to-many channel, attracting growing academic and managerial interest. Streamers use this platform to deliver detailed product information, demonstrate product usage, respond to consumer questions in real time, and design activities to foster engagement and

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Cite: Chai, S., Chang, Y., & Li, Y. (2026). Optimizing livestreaming sales: Configurational effects of time allocation across selling steps on product performance. Journal of Electronic Commerce Research, 27(3).

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interaction (Lu et al., 2018) (see Figure 1 in the Appendix). Globally, livestreaming commerce has expanded rapidly since 2020 (Chevalier, 2021). In China, the market size has grown to 1,237.9 billion yuan in 2020 and is expected to reach 4.9 trillion yuan by 2023 (Ma, 2021). Despite these substantial benefits for firms, important questions remain about how streamers communicate with consumers to effectively meet their needs and drive transactions, commonly referred to as salesperson communication effectiveness (Bharadwaj & Shipley, 2020; Hossain & Chonko, 2018; Williams et al., 1990).

Prior research has identified several key elements of salesperson communication effectiveness, including content, code, rule, and style (Andersen, 1972; Arli et al., 2018; Wongkitrungrueng et al., 2020; Xu & Ling, 2023; Yao et al., 2022). Among these, communication content, the subject matter or ideas conveyed to consumers, is the foundation upon which other elements are built. Existing studies primarily focused on what to say, such as content categories, sentiment, and thinking styles, and their effects on consumer engagement and persuasion (Bharadwaj et al., 2017; Pennebaker, 2013; Singh et al., 2018). More recently, research has begun to explore how much to say, or content volume, particularly in social media contexts. The results showed that message length can significantly impact engagement metrics such as likes and comments (Cuevas-Molano et al., 2021, 2022; De Vries et al., 2012; Sabate et al., 2014). However, little is known about the role of spoken content volume in real-time, interactive selling contexts. This gap is particularly salient in livestreaming commerce, where streamers must complete the whole selling process—including approach, presentation, overcoming objections, and close sales—within a limited time before consumers can make a purchase. These unique constraints create a critical challenge: streamers must decide how to allocate their limited time (measured by content volume in this research) across different selling steps to craft effective and persuasive selling.

Following the standardized selling process (Dubinsky, 1981), the product-level selling process in livestreaming commerce can be categorized into four steps: approach, presentation, overcoming objections, and close sales. While this framework has been validated in other contexts, its application to livestreaming commerce is nontrivial because of the medium's fast-paced and time-constrained nature. This raises a critical question: How should streamers allocate content volume across these four selling steps to improve product sales? Importantly, because these steps are interdependent and may exhibit complex substitution and complementarity relationships (Guenzi et al., 2011; Ingram et al., 2008; Persson, 1999), it is insufficient to analyze their net effects. Instead, we adopt a configurational analysis to capture the holistic and asymmetric combinations of selling steps that lead to high (or low) sales (Fiss, 2011; Ragin, 2008b).

Typical regression analysis and variance-based analysis, which examine the net effect of independent variables on an outcome (Pappas & Woodside, 2021; Woodside, 2013), are not applicable in our research context. Conversely, fuzzy-set qualitative comparative analysis (fsQCA), which focuses on the complex and asymmetric relations (combined effect) between the outcome and its antecedents (Fiss, 2011; Pappas & Woodside, 2021; Woodside, 2013), is applicable for exploring the configurational effect of content volume of the four selling steps on product sales.

Based on the equifinality principle of complexity theory and configuration theory, we propose that multiple configurations of content volume across the four selling steps can contribute to the same outcome: high/low product sales (Chuah et al., 2021; Miquel-Romero et al., 2020; Pappas & Woodside, 2021), which are aligned with the reciprocity norms of social exchange theory (Bagozzi, 1995; Blau, 1964; Zhang et al., 2016). To test our hypotheses, we analyzed livestreaming commerce data of snack products from a large e-commerce platform. We first applied the Latent Dirichlet Allocation (LDA) algorithm to classify fine-grained content into the four selling steps during each product's livestreaming session. We then used fsQCA to examine the configurational effect of content volume across the four selling steps on product sales.

Drawing on a configurational analysis, this research identifies multiple viable pathways through which streamers can allocate content volume across the four selling steps to achieve high product sales in livestreaming commerce. The results reveal three high-sales configurations (configurations 1a, 1b, and 1c), highlighting the complementarity of the approach and close sales steps, either both high or both low, as well as the substitution between the presentation and overcoming objections steps, where emphasizing one while minimizing the other can be effective. Among these, the configuration that prioritizes the presentation step while minimizing both the approach and close sales steps demonstrates the highest raw and unique coverage, suggesting that a transaction-oriented strategy centered on presentation may be particularly effective for snack products in time-constrained livestreaming contexts. Conversely, a misaligned configuration (configuration 2), characterized by high approach but low close sales content, is sufficient for low product sales, underscoring the importance of alignment and balance across steps. These findings reaffirm the need for a holistic and flexible approach to managing the selling process in livestreaming commerce.

This research makes important contributions to the literature on livestreaming commerce and salesperson communication effectiveness. First, it advances livestreaming commerce research by unpacking the effectiveness of streamers' communication through the lens of the standardized selling process. By decomposing communication content into four distinct selling steps and examining their combined effects, we demonstrate how different allocations of content volume across these steps shape sales outcomes. Second, we enrich the literature on salesperson communication effectiveness in the real-time retailing context by focusing on the role of streamer's communication content volume, a dimension that has received scant attention compared to research on what to say. Drawing on fsQCA, we reveal the configurational and equifinal nature of communication effectiveness, showing how complementary and substitutive patterns among selling steps jointly influence product sales. Notably, this is among the first empirical applications of fsQCA to examine the configurational effects of communication in livestreaming, offering a novel methodological perspective for future research. Finally, our findings provide actionable insights for managers and practitioners, highlighting how to design and adjust livestreaming scripts by strategically balancing content volume across the four selling steps to improve sales performance.

2. Theoretical development

2.1 Livestreaming commerce

Livestreaming commerce, which integrates real-time livestreaming with e-commerce, has emerged as an innovative and interactive sales channel (Cai & Wohn, 2019; Hamilton et al., 2014). Unlike traditional online mass marketing, livestreaming commerce facilitates two-way, synchronous communication between sellers and consumers, enabling real-time information exchange and fostering more engaging interactions (Cui et al., 2024; Hamilton et al., 2014; Wang et al., 2022b). Beyond its transactional function, livestreaming also incorporates entertainment elements—such as humor, games, and giveaways—which significantly influence consumers' shopping behavior by enhancing enjoyment and engagement (Li et al., 2019; Lu et al., 2018; Wang et al., 2022a).

Previous research on livestreaming commerce has made notable progress in recent years, but streamer-related factors remain underexplored. Specifically, existing research primarily focused on three streams of inquiry: consumers' motivations, livestreaming characteristics, and streamer attributes. The first stream highlights consumers' hedonic and utilitarian motivations for participating in livestreaming commerce (Cai & Wohn, 2019; Huang et al., 2024; Wongkitrungrueng et al., 2020). For example, Wongkitrungrueng et al. (2020) and Huang et al. (2024) demonstrated that both enjoyment-driven and goal-oriented motivations shape consumer purchase intentions. The second stream examines how livestreaming characteristics affect outcomes (e.g., Asante et al., 2024; Lyu et al., 2024; Tong et al., 2022; Xiao et al., 2023; Zhang et al., 2024). For instance, Tong et al. (2022) found an inverted U-shaped relationship between background visual complexity and purchase intention, while Zhang et al. (2024) showed that the number of products showcased and audience stay-time similarly exhibit nonlinear effects on sales. The third stream focuses on the personal attributes of streamers, such as gender, expertise, experience, and emotional expression (e.g., Bharadwaj et al., 2022; Miranda et al., 2024; Xu et al., 2020; Ye et al., 2024). Studies have shown that expertise outweighs attractiveness in driving purchase intentions (Guo et al., 2022), and experienced streamers or those with larger follower bases tend to perform better (Meng et al., 2021; Song et al., 2021). Other research highlights the role of emotions, finding that emotional displays exhibit inverted U-shaped effects on sales (Bharadwaj et al., 2022).

Although these studies have advanced our understanding of livestreaming commerce, research on how streamers effectively communicate with consumers remains limited. Prior work has begun to examine communication approaches and styles. For example, Wongkitrungrueng et al. (2020) identified a variety of sales approaches and persuasive strategies, while Yao et al. (2022) found that social-oriented language is more effective for experience goods than for search goods. Luo et al. (2024) further distinguished between informative and affective content and their effects on engagement. However, this line of research has primarily focused on the style and type of communication, often overlooking the volume of communication content—that is, how much a streamer says, and how this volume is allocated across the different stages of the selling process.

To better understand the role of communication content volume in livestreaming commerce, it is helpful to draw on insights from the broader salesperson communication literature, which has long examined how communication content and its delivery affect sales outcomes.

2.2 Salesperson communication effectiveness

Previous research on salesperson communication primarily focused on four elements: content, code, rule, and style (Andersen, 1972). Communication content, referring to the subject matter or idea, determines what to say. Communication code encompasses the verbal and nonverbal forms of content, indicating how and when to speak. Communication rule combines content and code, specifying how and when to communicate what. Communication style, developed over time through frequent use of content, code, and rules, represents a consistent "pattern."

All research on salesperson communication effectiveness fundamentally builds on content, which is delivered through appropriate codes and rules and eventually shapes the overall communication style. These elements have continually evolved to adapt to changes in technology, competitive environment, and consumer knowledge (e.g., Arli et al., 2018; Bharadwaj & Shipley, 2020; Das, 2016; DeCormier & Jobber, 1993). For example, content has been standardized through the widely adopted seven steps of selling, formalized in the 1980s: (1) prospecting, (2) preapproach, (3) approach, (4) presentation, (5) overcoming objections, (6) closing the sale, and (7) follow-up (Dubinsky, 1981). This model has since evolved with technological and market changes (Inks et al., 2019; Moncrief & Marshall, 2005) but remains a cornerstone of sales training and research in the present day (Castleberry & Tanner, 2018; Lancaster & Jobber, 2015; Manning et al., 2017; Kadić-Maglajlić et al., 2021). In parallel, scholars have explored how and when to deliver content through influence tactics, such as information exchange, recommendations, promises, ingratiation, and inspirational appeals (Frazier & Summers, 1984; Hochstein et al., 2018; McFarland et al., 2006; Spiro & Perreault, 1979; Venkatesh et al., 1995). Building on this, the concept of adaptive selling emerged, emphasizing the dynamic adjustment of content, code, and tactics to fit consumer needs and knowledge (DeCormier & Jobber, 1993; Hughes et al., 2013; Román & Iacobucci, 2010). These changes have ultimately shifted sales communication styles from transactional to more relationship-oriented approaches (Arli et al., 2018; Sheth & Parvatiyar, 1995; Verma et al., 2016).

Among these elements, communication content—the foundation of all other elements—has received comparatively less attention in recent years. Existing research on content has focused largely on what to say, such as the impact of content categories (e.g., informative vs. affective), sentiment, and thinking styles on consumer engagement and persuasion (Bharadwaj et al., 2017; Pennebaker, 2013; Singh et al., 2018). More recently, a stream of research in social media contexts has begun to explore how much to say, or content volume, demonstrating that message length can significantly affect user engagement metrics like likes and comments (Cuevas-Molano et al., 2021, 2022; De Vries et al., 2012; Sabate et al., 2014). These findings highlight that the quantity of content, in addition to its type and tone, plays a critical role in shaping consumer responses.

However, research on spoken content volume remains limited, particularly in time-constrained selling environments such as livestreaming commerce. In livestreaming sessions, streamers face strict time limits for each product pitch and must complete the entire selling process—including approach, presentation, overcoming objections, and close sales—before consumers can make a purchase. This unique constraint creates a natural tension: streamers must decide how to allocate their limited time (measured by content volume in this research) across different selling steps while maintaining an effective and persuasive overall product selling. Addressing this gap not only extends our understanding of salesperson communication content beyond what to say into how much to say, but also provides actionable insights for optimizing sales performance in emerging retail channels.

2.3 Configurational effect of the content volume of the four selling steps

While the conventional selling model includes "seven steps" (Dubinsky, 1981), the livestreaming selling process typically encompasses only four steps, including (1) approach, (2) presentation, (3) overcoming objections, and (4) close sales. According to Dubinsky (1981) and Moncrief & Marshall (2005), the "prospecting step" involves identifying target customers; the "preapproach step" entails collecting customer information and understanding their needs; the "approach step" initiates contact and builds a relationship, often through greetings and providing a token gift; the "presentation step" introduces the product's attributes, benefits, and value; the "overcoming objections step" addresses customer concerns, often through factual explanations, testimonials, and comparative examples; the "close sales step" involves asking for orders and finalizing transactions; the "follow-up step" involves providing post-sales service.

In the context of livestreaming commerce, the first two steps of the selling process—prospecting and preapproach—are typically completed through other channels before the livestreaming session, while the follow-up step generally occurs afterward through yet other channels. Specifically, retailers often identify and target potential customers (prospecting) using tools such as customer databases, social media advertising, or search engine marketing. They then gather customer information and insights (preapproach) via online surveys, prior purchase data, or direct messaging platforms (e.g., email, WeChat groups). After the livestreaming session, follow-up activities are usually conducted through customer service hotlines, live chat, loyalty apps, or in-store services. These practices reflect the omnichannel nature of modern retailing (Lemon & Verhoef, 2016; Verhoef et al., 2015), where different stages of the selling process are distributed across multiple touchpoints and channels. For example, consumers often engage in search-online-purchase-offline (Li et al., 2023) or buy-online-pick-up-in-store (Li et al., 2024) journeys, illustrating how different channels are strategically assigned to different steps of the customer journey. Therefore, our focus on the four steps that actually occur during the livestreaming event itself—approach, presentation, overcoming objections, and close sales—is both theoretically grounded and contextually appropriate, reflecting the role of livestreaming as one integrated but bounded part of the broader omnichannel selling process.

This research examines the configurational effect of content volume across the four selling steps in livestreaming commerce. In practice, product selling is a combination of interconnected stages (Guenzi et al., 2011; Ingram et al., 2008; Persson, 1999). The selling steps are correlated and should not be analyzed in isolation (Persson, 1999).

Therefore, it is essential to examine the combined effect (configurational effect) rather than the net effect of these steps (e.g., Delery & Doty, 1996; Fiss, 2007; Park & Mithas, 2020; Sun, 2021).

Complexity theory and configuration theory highlight the principle of equifinality, which posits that multiple configurations of antecedent conditions can lead to the same outcome (Fiss, 2007; Ragin, 2008b; Woodside, 2014). It provides us with a holistic understanding of the effect of multiple variables (El Sawy et al., 2010; Fiss, 2011). Applied to the context of livestreaming commerce, this perspective suggests that different patterns of salesperson communication content volume across the four key sales steps—approach, presentation, overcoming objections, and close sales—may each provide viable pathways to high product sales. Specifically, it is plausible that not all steps or levels of content are universally necessary; rather, certain steps, when combined in specific ways, may form sufficient conditions for success. This theoretical lens underscores the complex and interdependent nature of salesperson communication in the livestreaming context and provides a foundation for examining how varying combinations of content volume across selling steps can contribute to desirable sales outcomes. Thus, we assume that there are different combinations of the content volume of the four selling steps that can lead to high/low product sales in the livestreaming commerce context.

2.4 Reciprocity norms in the exchange process

The exchange process in livestreaming commerce is best characterized as reciprocal rather than negotiated. Social exchange theory, which emphasizes social interaction within the exchange process, distinguishes between negotiated and reciprocal forms of exchange (Blau, 1964; Kim et al., 2022; Molm, 1991, 2003). Negotiated exchange focuses on joint decision-making and formal agreements, where the costs and benefits are explicitly determined and agreed upon by both parties at the same time (Molm, 2003). In contrast, reciprocal exchange involves actors initiating beneficial acts without knowing if, when, or how the other party will reciprocate, and is more relational, informal, and self-reinforcing (Molm, 1991, 2003). In the livestreaming context, streamers initiate interactions, provide product advice, and offer entertainment, while consumers independently decide when and what to buy. This asynchronous and voluntary decision process aligns more closely with the logic of reciprocal rather than negotiated exchange. Unlike the traditional one-sided and non-reciprocal parasocial relationship, livestreaming fosters direct, two-way interactions that cultivate reciprocal communication between sellers and consumers (Kowert & Daniel, 2021). Users who receive a community gift during the livestreaming exhibit more social engagement with streamers (Chaudhry et al., 2025). Similarly, streamers tend to provide a reciprocal response to consumers' tipping behavior by showing happy facial expressions (Yao et al., 2024). Moreover, the reciprocal value from streamers can mitigate consumers' dissatisfaction and complaint intention in the face of product or service problems (Huang & Ma, 2024).

In light of these findings, we argue that the four selling steps in the livestreaming sales process—approach, presentation, overcoming objections, and close sales—can activate different types of reciprocity norms that promote exchange (purchase). Reciprocity, referring to an obligation to respond in kind to the actions of others, encompasses two distinct forms: goodwill reciprocity and equivalence reciprocity (Houston & Gassenheimer, 1987). Goodwill reciprocity involves mutual acknowledgment of positive actions driven by shared interests, assessed through a reciprocal exchange of gratifications. Equivalence reciprocity is rooted in proportionality and fairness, where the effort or benefit provided by one party is expected to be matched by a comparable response (Gouldner, 1960; Hoppner & Griffith, 2011; Kim et al., 2022; Swärd, 2016).

The approach step, which focuses on initiating contact and expressing goodwill through greetings or small tokens, is theorized to elicit goodwill reciprocity, thus promoting exchange. This is supported by findings that goodwill actions, even minor ones, can promote trust and generate an obligation to reciprocate (Blau, 1964; Cook et al., 2013; Swärd, 2016). The presentation and overcoming objections steps, which involve presenting product attributes and addressing concerns, are theorized to evoke equivalence reciprocity, as they signal substantive effort and value commensurate with the desired exchange (Blau, 1964; Cook et al., 2013; Hoppner & Griffith, 2011; Luo et al., 2023) Equivalence reciprocity implies reliability and stability of the exchange (Hoppner et al., 2015; Swärd, 2016). Thus, the presentation and overcoming objections steps can promote exchange by eliciting equivalence reciprocity.

Notably, the presentation and overcoming objections steps are expected to be partially substitutive because both contribute to perceptions of equivalence reciprocity, aligning with the principle of equifinality in complexity theory—that different configurations of antecedent conditions can lead to the same outcome (Chuah et al., 2021; Miquel-Romero et al., 2020). However, the approach step, enhancing goodwill reciprocity, can complement the equivalence reciprocity evoked by the presentation and overcoming objections steps to enhance the perception of the whole reciprocity. Therefore, we propose:

Proposition 1. A configuration with a high content volume of the presentation, a low content volume of the overcoming objections, and a high content volume of the approach can cause high product sales.

Proposition 2. A configuration with a low content volume of the presentation, a high content volume of the overcoming objections, and a high content volume of the approach can cause high product sales.

Furthermore, the close sales step, which involves directly requesting orders, is likely to succeed only when preceded by sufficient goodwill in the approach step because goodwill legitimizes subsequent requests. This is consistent with the door-in-the-face effect, which indicates that showing goodwill by conceding a big request can persuade agreement with a small request (Cialdini et al., 1975; Genschow et al., 2021; Lecat et al., 2009). Thus, we propose:

Proposition 3. The high content volume of the close sales step must correspond to the high content volume of the approach, thereby resulting in high product sales.

3. Methodology

We aim to investigate the configurational effect of the content volume of the four selling steps on product sales. Typical regression analysis and variance-based analysis are used to quantify the average net effects of independent variables on an outcome using linear models, and the regression analysis struggles to model more than 3-way interactions due to interpretability loss and statistical inefficiency (Pappas & Woodside, 2021; Ragin, 2008b; Woodside, 2013). These two methods fall short in examining the combined effect of these interrelated variables. Unlike the above two methods, configuration analysis allows for the exploration of interrelationships between multiple variables (Delery & Doty, 1996; Fiss, 2007; Gligor & Bozkurt, 2020). This holistic approach provides a comprehensive understanding of the effects of these variables, considering that their combined conditions could lead to various outcomes (Fiss, 2007; Ragin, 2008b; Shao, 2024; Woodside, 2014).

QCA, which is a method based on set theory and seamlessly combines qualitative and quantitative approaches, is suitable to address the configuration problem (Diwanji, 2023; Ragin, 2000, 2008b; Rihoux & Ragin, 2009). QCA incorporates two key features: equifinality and causal asymmetry (Ragin, 2000; Ragin, 2008b). Equifinality implies that different configurations can yield the same result, while causal asymmetry suggests that configurations leading to a specific result differ from those leading to its absence (Fiss, 2007). QCA enables the exploration of how multiple variables combine to have a configurational effect on the outcome of interest (Ragin, 2008b). It can also identify the relative importance of different combinations and conditions within these combinations (Fiss, 2011; Pappas & Woodside, 2021; Sukhov et al., 2023). Compared with regression analysis, QCA asks “What condition-sets cause Y?” while regression tests “What is X’s average effect on Y?”, making it superior for analyzing complex multi-conjunctural causality in small-to-medium samples. Consequently, we utilize QCA to explore the configurational impact of the content volume of the four selling steps on product sales. Given that our data consists of continuous variables, we chose fsQCA[2] to conduct the configurational analysis. In the next step, we will introduce our data and employ fsQCA to conduct a comprehensive configuration analysis.

3.1 Sample and data

Livestreaming commerce encompasses both enterprise livestreaming commerce and influencer livestreaming commerce[3] (iResearch, 2021). Enterprise livestreaming commerce, conducted by the brand itself, exclusively sells products from its own brand. In China, enterprise livestreaming commerce constituted 32.1% of the total livestreaming commerce market in 2020 and is projected to reach 50% by 2023. Given its increasing importance, we focused our research on enterprise livestreaming commerce.

Our data were sourced from a leading e-commerce platform in China. According to KPMG and AliResearch (2020), food ranks as the third-largest product category in livestreaming commerce, with snacks being the most favored among livestreaming commerce users in 2021 (Chevalier, 2021). Based on this, we selected one of the largest snack companies engaging in livestreaming commerce on the e-commerce platform as our research subject. To ensure representativeness and avoid event-driven bias, we sampled a regular week without special holidays or festivals, from July 6 to July 12, 2021.

During the seven days, two trained research assistants monitored both the company’s livestreaming sessions and brand store on the platform. Video recordings of all livestreaming sessions were captured using Open Broadcaster Software. In total, videos from seven livestreaming sessions were collected. The assistants recorded the start and end times of each product segment within each session[4], recorded sales data at 5-minute intervals during each session, and gathered information on product prices and monthly sales.

The initial dataset included 534 products. We first excluded non-product items (e.g., coupons) and those without clearly defined livestreaming times, leaving 117 products. Following McWilliams and Siegel’s (1997)

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[2] CsQCA is often used to analyze binary data, mvQCA for multivalued data, and fsQCA for continuous data.

[3] Influencer livestreaming commerce is a type of e-commerce where individual influencers sell various brands of products through live streaming.

[4] The number of products was limited in each livestreaming session, and each product was arranged to be sold in a specific time.

recommendation to avoid confounding events, we further excluded products with livestreaming durations exceeding one hour. The final sample comprised 104 products.

3.2 Measurements

Dependent variable: Product sales units We collected the sales data from the start of the product livestreaming to 5 minutes after the end of the product livestreaming as the dependent variable. The reason for this choice is based on the fact that the sales data during the product livestreaming is aggregated in 5-minute intervals. Considering the potential lag in sales immediately after the product livestreaming ends, we also include the sales data of the 5-minute interval following the end of the livestream.

Independent variable: Content volume distribution of the four selling steps To construct the independent variables, we employed a two-stage process combining Automatic Speech Recognition (ASR) and Latent Dirichlet Allocation (LDA). First, the video recordings of the seven livestreaming sessions were converted into audio files, which were then transcribed into text using ASR. The content text spoken by the streamer was transcribed at the sentence level, with each sentence occupying a separate line in the dataset and annotated with its corresponding start and end time stamps. This process produced a total of 84,592 sentence-level texts, reflecting the full scope of the streamers' spoken content.

Given the scale and complexity of the dataset, manual coding would have been infeasible and prone to subjective bias, while supervised machine learning approaches would have required predefined labeled data and imposed researcher-determined categories. To avoid such limitations and to uncover the latent, emergent structure of the spoken content in a data-driven manner, we applied LDA—an unsupervised topic modeling technique widely used for extracting semantic patterns from large text datasets (Blei et al., 2003; Gupta et al., 2022; Saura et al., 2022). Specifically, LDA was used to identify the underlying topic of each sentence within the product-specific livestreaming period.

We partitioned the transcribed text into two subsets: one for training the LDA model to estimate the topic distributions, and one for evaluating model fit. Using the perplexity criterion, we determined that a ten-topic solution best balanced interpretability and model performance (see Table 1 for representative topic terms and descriptions). Since LDA does not inherently assign semantic labels to topics (Wang et al., 2015), we manually interpreted and labeled each topic based on its most representative words, consistent with established procedures (Hagen, 2018; Slof et al., 2021).

To prepare for subsequent analysis, we first aggregated the sentence-level topic assignments to the product level. By aligning sentence timestamps with product livestreaming intervals, we derived the distribution of sentences across the ten topics for each of the 104 products. This yielded, for each product, both the absolute sentence counts and the proportional distribution across the ten topics.

To provide a comparative benchmark for our topic categorization, we conducted an exploratory factor analysis (EFA) using the product-level topic proportions as continuous variables. The analysis was performed in R Studio (version 4.5.1). The Kaiser-Meyer-Olkin (KMO) measure was 0.96, well above the recommended threshold of 0.6, and Bartlett's test of sphericity was significant ($p < 0.001$), confirming the suitability of the data for factor analysis. However, following the eigenvalue-greater-than-one criterion, only one factor was extracted, explaining 96.7% of the variance (see Table 2). This result indicates that, from a purely statistical standpoint, the ten topics could be consolidated into a single dimension. However, this conclusion is difficult to reconcile both theoretically and practically, as it overlooks the distinct communicative goals each topic represents (e.g., building rapport versus conveying specifications). Consequently, we deemed the EFA outcome theoretically simplistic and inadequate for capturing the nuanced semantic structure essential to our research context.

Given the theoretical relevance of the established selling framework, we then categorized the ten topics into the four standardized selling steps—approach, presentation, overcoming objections, and close sales—based on the conceptual definitions of the steps and the semantic content of each topic (see Table 3). This allowed us to compute, for each product and each selling step, two key measures: the absolute content volume (number of sentences assigned to the step) and the relative content volume (proportion of sentences in the step relative to the total sentences across all steps). The relative content volume of the four steps served as the independent variables in subsequent analyses. This measure facilitates a fair comparison between products by focusing on how streamers distribute their limited speaking time across the selling steps, a key concern in the time-constrained context of livestreaming commerce.

Table 1. Results of LDA Topic Modeling

Topic	Name Assigned to Topic	Topic Terms	Topic explanations according to the raw text data and topic terms
1	Free chat	Cell phone, hair color, left, happy, game, etc.	Streamers engage with consumers on various topics, including playing games, discussing the

			streamer's hair color and clothing, and talking about other streamers.
2	Answering questions about product value	Again, attention, product, worth, good choice, etc.	Streamers discuss the value of products with consumers, emphasizing factors such as the product being a good choice and highlighting its nutritional benefits.
3	Answering questions about the promotion	Promotion activity, pillow, gift, engagement, want, etc.	Streamers address questions related to promotions, covering topics such as promotional gifts, product inventory, and details about recharge promotions.
4	Sweepstakes	List, lucky guy, drawing, time, congratulations, etc.	Streamers actively encourage consumers to participate in lottery activities, providing information on the timing of the lottery, the prizes available, and the list of winners.
5	Answering questions about product attributes	Gram, pack, technique, raw material, taste, etc.	Streamers respond to queries about product attributes, including details such as the weight of each product package, packaging specifications, and information about raw materials.
6	Free interaction	Share, follow, interaction, question, engagement, etc.	Streamers motivate consumers to participate by asking questions, following the stream, sharing the livestreaming room, and occasionally offering gifts and conducting lottery activities.
7	Order recommendation	Recommend, order, coupon, free shipping, buy, etc.	Streamers inspire and prompt consumers to place orders, using strategies like offering discounts for immediate orders, encouraging quick purchases, and suggesting buying multiple packages for added benefits.
8	Answering questions about the product list	Out of the list, today, broad bean, nut, list number, etc.	Streamers address questions about product lists and promotional items, providing information such as the availability of flash sale products, whether certain products are included in promotions, and specifying products with exclusive benefits for livestreaming viewers.
9	Product introduction	High quality, taste, pack, price, our product, etc.	Streamers introduce products to consumers, sharing details like the quantity in a package, the variety of nuts in a product, the use of specific raw materials (e.g., red pepper), and highlighting the highest quality nuts in a gift box.
10	Greetings	Welcome, babies, good morning, room, new, etc.	Streamers greet consumers with friendly phrases, including "hello everyone," extending a welcome to specific individuals, and welcoming new customers to the livestreaming.

Table 2. Exploratory Factor Analysis Results (N = 104)

Topics	**Factor Loading**	**Variance Explained**
Topic 1	0.981	96.7%
Topic 2	0.980	
Topic 3	0.990	
Topic 4	0.983	
Topic 5	0.989	
Topic 6	0.989	
Topic 7	0.971	
Topic 8	0.980	

Topic 9	0.988
Topic 10	0.989

Table 3. Topic Classification

Selling Step	Topic
Approach	1, 4, 6, 10
Presentation	9
Overcoming Objections	2, 3, 5, 8
Close Sales	7

3.3 fsQCA analysis

FsQCA serves as a widely used configuration analysis tool grounded in set theory and Boolean logic (Fiss, 2011; Ong & Johnson, 2021; Ragin et al., 2008). It effectively explores the configuration relationship (combined effect) between sets of multiple independent variables and outcome variables, identifying the effective configurations of the independent variables for an outcome while embracing causal asymmetry (e.g., success/failure requiring distinct paths) and equifinality (multiple solutions to one outcome) (e.g., Elshaer et al., 2024; Fiss, 2011; Greckhamer et al., 2008; Hew et al., 2023; Ragin, 2008b). Next, we delve into the details of fsQCA analysis.

Data calibration The initial step in fsQCA involves calibrating all variables to fuzzy-set membership scores ranging from 0 to 1, which reflect the degree to which each case belongs to a theoretically defined set (Ragin, 2008b; Rihoux & Ragin, 2009). Calibration does not dichotomize continuous variables into binary categories; rather, it transforms raw data into continuous membership scores anchored in substantive and theoretical knowledge of the phenomenon under study. In this scale, a score of 1 indicates full membership in the set, a score of 0 indicates full non-membership, and a score of 0.5 represents maximum ambiguity, where a case is neither clearly “in” nor “out” of the set. These thresholds are typically determined using the direct calibration method, which requires defining three qualitative anchors—fully in, fully out, and the crossover point—based on empirical and theoretical justification (Ragin, 2008b; Rihoux & Ragin, 2009). This approach enables researchers to retain the continuous nuances of raw data while recasting them into a structure aligned with set-theoretic principles (Ragin, 2008a).

While commonly used percentile thresholds such as 75th/25th or 90th/10th percentiles are acceptable, the selection of calibration thresholds must also align with the sample characteristics (Campbell et al., 2016; Misangyi & Acharya, 2014; Ong & Johnson, 2021). We conducted a normal analysis of our sample, which revealed that the data was skewed to the left. Consistent with previous research, we set the 85th percentile as full membership, the 15th percentile as full non-membership, and the 50th percentile as the crossover point (Campbell et al., 2016; Pappas et al., 2017). This calibration strategy combines theoretical justification and empirical distributional properties to minimize subjectivity and ensure that the thresholds meaningfully reflect the degree of set membership, consistent with established fsQCA practices (Ragin, 2008b; Rihoux & Ragin, 2009). Table 4 shows the detailed calibration rules for all constructs, conducted using fsQCA 3.0 (Pappas & Woodside, 2021).

Table 4. Overview of the Calibration Rules

Construct	Calibration rule	
Approach (APP)	if APP $\geq$ 0.52	1 (full membership)
	if APP $\leq$ 0.40	0 (full non-membership)
	if APP = 0.46	0.5 (crossover point)
Presentation (PRE)	if PRE $\geq$ 0.10	1 (full membership)
	if PRE $\leq$ 0.04	0 (full non-membership)
	if PRE = 0.07	0.5 (crossover point)
Overcoming objections (OB)	if OB $\geq$ 0.42	1 (full membership)
	if OB $\leq$ 0.32	0 (full non-membership)
	if OB = 0.36	0.5 (crossover point)
Close sales (CS)	if CS $\geq$ 0.13	1 (full membership)
	if CS $\leq$ 0.06	0 (full non-membership)
	if CS = 0.09	0.5 (crossover point)
Product sales（PS）	if PS $\geq$ 23.50	1 (full membership)
	if PS $\leq$ -10.00	0 (full non-membership)
	if PS = 0.00	0.5 (crossover point)

Notes: The 85th percentile is the threshold for the full membership, the 15th percentile is the threshold for the full non-membership, and the 50th percentile is the threshold for the crossover point.

Analysis of necessary conditions The second step involves necessary condition analysis, assessing whether the four conditions[5] are necessary for an outcome. The criterion for necessary conditions is that the consistency threshold must exceed 0.9 (Fiss, 2007; Tóth et al., 2015). However, our analysis revealed that the consistency thresholds for all conditions were below 0.9, suggesting that the four conditions were not necessary conditions. Table 5 shows the necessary condition analysis results.

Table 5. Overview of the Necessary Conditions

Condition	**Product sales**			
	Presence		**Absence**	
	cons.	cov.	cons.	cov.
Approach	0.57	0.61	0.67	0.62
~Approach	0.64	0.69	0.58	0.54
Presentation	0.62	0.65	0.60	0.55
~Presentation	0.57	0.62	0.62	0.58
Overcoming objections	0.61	0.67	0.56	0.53
~Overcoming objections	0.58	0.60	0.65	0.59
Close sales	0.57	0.66	0.57	0.56
~Close sales	0.62	0.62	0.66	0.57

Notes: "~" indicates a logical NOT (the absence of a construct); cons. = consistency; cov. = coverage.

Analysis of sufficient conditions (truth table analysis) After calibrating the data, values at the crossover point (0.5) can lead to information loss, because in fsQCA, cases with a membership score exactly equal to 0.5 are treated as fully ambiguous and are excluded from the truth table analysis (Ragin, 2008b). To address this issue, following Fiss's (2011) recommendation, we added a constant of 0.001 to all conditions with scores of 0.5, ensuring that each case could be classified as either more in or more out of the set and thus included in the analysis.

We constructed the truth table using fsQCA 3.0, where each row represents a unique combination of conditions. Given the four conditions (the four selling steps), the truth table consisted of 16 possible configurations (2^k; k = the number of conditions) (Greckhamer et al., 2008; Ong & Johnson, 2021).

The truth table was then sorted based on frequency, consistency, and counterfactual analysis (Pappas & Woodside, 2021; Ragin, 2008b). First, we set the frequency threshold at 3, following previous recommendations for studies with sample sizes exceeding 150 (Fiss, 2011; Ragin, 2008b). Although our sample size was 104 (below 150), the truth-table results showed no viable configurations when the threshold was set below 3. Therefore, we maintained a frequency threshold of 3. Second, we used the consistency threshold to determine whether the condition configuration was sufficient for the result. We applied a consistency threshold of 0.8 along with a minimum proportional reduction in inconsistency (PRI) of 0.5. Third, we conducted a counterfactual analysis to examine whether this condition is an intermediate solution, meaning that one condition is always present or absent in the chosen configuration. Given the earlier finding of no necessary conditions, we adopted a "Present or Absent" approach for all conditions in fsQCA 3.0, allowing for a thorough examination of the results. Further details on counterfactual analysis can be found in Fiss (2011) and Pappas and Woodside (2021). The results of the fsQCA are presented in the following section.

3.4 Results

Overview of the results FsQCA produces three types of solutions: complex, parsimonious, and intermediate. The complex solution includes all empirically observed configurations, some of which may be impractical. The parsimonious solution simplifies the complex solution by incorporating both easy and difficult counterfactuals, identifying configurations that are present in all three solutions. The intermediate solution, based on easy counterfactuals only, distinguishes between core and peripheral conditions: conditions appearing in both the intermediate and parsimonious solutions are deemed core conditions, indicating strong causal relationships, whereas those unique to the intermediate solution are considered peripheral conditions, reflecting weaker causal links. Table 6 reports the fsQCA results based on the intermediate and parsimonious solutions.

[5] Each condition comprises two states: presence and absence. The presence represents the condition itself, while the absence is the logical negation of the condition.

Following Fiss (2011), condition presence (high condition[6]) is represented by a black circle (●), absence (low condition) by a crossed-out circle (⊗), and "do not care" by a blank space. Circle size distinguishes core conditions (large circles) from peripheral conditions (small circles). The results include solution coverage and solution consistency. Solution coverage refers to the degree to which the configuration can explain the outcome presence (absence), which is similar to the R-square in regression (Ragin, 2008b; Woodside, 2013). Solution consistency refers to the degree of consistency of the results obtained for all configurations. The suggested solution consistency is 0.8 (Dul, 2016; Fiss, 2011; Mendel & Korjani, 2012; Pappas & Woodside, 2021). As shown in Table 6, both solution coverage and consistency exceed 0.8.

Table 6. Overview of the Sufficient Conditions

	Product sales			
	High			**Low**
Selling step conditions	**Con1a**	**Con1b**	**Con1c**	**Con2**
Approach	●	●	⊗	•
Presentation	●	⊗	●	●
Overcoming objections	⊗	●	•	⊗
Close sales	●	●	⊗	⊗
Consistency	0.80	0.80	0.83	0.82
Raw coverage	0.24	0.17	0.29	0.32
Unique coverage	0.11	0.05	0.16	0.32
Solution coverage		0.47		0.32
Solution consistency		0.80		0.82

Notes: "Con" indicates "Configuration". ● indicates the presence of core condition; ⊗ indicates the absence of core condition; • indicates the presence of peripheral condition; ⊗ indicates the absence of peripheral condition.

Configurational results of high and low product sales We identified three configurations (1a, 1b, and 1c) associated with high product sales and one configuration (2) associated with low product sales, providing streamers with strategic choices (see summary in Table 7). The Boolean algebra algorithm expresses these configurations as:

APP*PRE*~OB*CS+APP*~PRE*OB*CS+~APP*PRE*OB*~CS ⟶ HPS

APP*PRE*~OB*~CS ⟶ LPS

Here, "~" denotes the absence of the condition, "*" represents the logical "and," and "+" represents the logical "or." APP is approach, PRE is presentation, OB is overcoming objections, CS is close sales, HPS is high product sales, and LPS is low product sales.

Table 7. Summary of the Configuration Results

Configuration	Approach	Presentation	Overcoming objections	Close sales	Product sales	Raw coverage
Con1a	**High**	**High**	Low	**High**	High	0.24
Con1b	**High**	Low	**High**	**High**	High	0.17
Con1c	**Low**	**High**	High	**Low**	High	0.29
Con2	High	**High**	**Low**	**Low**	Low	0.32

Notes: "Con" indicates "Configuration". The bolded conditions mean core conditions. The nonbolded conditions mean peripheral conditions. The presentation and overcoming objections are substitutional relations. The approach and close sales are complementary relations.

Next, we delve into detailed explanations for each configuration:

Configuration 1a: Core conditions encompass high content volume of approach, presentation, and close sales. Low content volume of overcoming objections is a peripheral condition. In this configuration, streamers should allocate more time to approach, presentation, and close sales, deeming overcoming objections less crucial.

Configuration 1b: Core conditions include high content volume of approach, overcoming objections, and close sales. Low content volume of presentation is a peripheral condition. Streamers, in this scenario, should prioritize time for approach, overcoming objections, and close sales, considering presentation less essential.

6 Following previous research, we used "high" and "low" to represent the "presence" and "absence" of one condition, respectively (Gabriel et al., 2018; Ong & Johnson, 2021).

Configuration 1c: Core conditions include low content volume of approach, high content volume of presentation, and low content volume of close sales. High content volume of overcoming objections is a peripheral condition. This suggests that, during product livestreaming, streamers should emphasize the presentation step, minimizing content in approach and clos sales, while overcoming objections is less critical.

Configuration 2: Core conditions include high content volume of presentation, low content volume of overcoming objections, and low content volume of close sales. High content volume of approach is a peripheral condition. It suggests that failing to align the approach and close steps as consistent, high- or low-level core conditions results in lower product sales. The persistence of the ineffective configuration underscores a potential misapplication of scripting in practice, where streamers may deploy a mismatched sequence of selling steps—such as building rapport without a subsequent call to action—thereby undermining the effectiveness of their pitch.

Discussion about the fsQCA results This research examines how different combinations of content volume across the four selling steps jointly shape product sales outcomes in livestreaming commerce. Rather than evaluating the individual importance of each step, our findings highlight the configurational logic of sales communication, demonstrating that it is the alignment, complementarity, and trade-offs among steps that determine effectiveness.

First, all three configurations leading to high product sales support Proposition 3, emphasizing the need for alignment between the content volume of the approach and close sales steps. Configurations 1a and 1b show that a high–high combination of approach and close sales steps can drive high sales, while Configuration 1c shows that a low–low combination is also effective under certain conditions. This pattern suggests that these two steps function as interdependent anchors of the selling process, and misalignment between them, as illustrated by Configuration 2, which pairs a high approach (peripheral) with a low close sales (core), is detrimental to sales. This underscores the configurational nature of the selling process, in which these two steps complement each other and need to be coordinated, rather than optimized in isolation.

Second, the findings illustrate how different combinations of the presentation and overcoming objections steps can complement the approach–close sales alignment in distinct ways. Proposition 1 is supported by Configuration 1a, where high presentation content complements high approach and close sales content, while minimizing overcoming objections. In contrast, Proposition 2 is supported by Configuration 1b, which combines high overcoming objections content with high approach and close sales content, while reducing presentation. These alternative combinations reflect a substitutional relationship between the presentation and overcoming objections steps. Importantly, this substitutional relationship is particularly valuable in livestreaming contexts, where the time available for each product is limited. By strategically shifting emphasis between presentation and overcoming objections, streamers can tailor their message to the situation while making efficient use of the constrained time.

Third, Configuration 1c presents yet another viable combination, where high presentation content volume is paired with low content volume in both the approach and close sales steps, and overcoming objections is deemphasized. This configuration demonstrates that even when the approach (goodwill reciprocity) and close sales steps are minimized, a strong focus on presentation (equivalence reciprocity) alone can be sufficient to drive high product sales. Thus, our findings illustrate the flexibility of different combinations and support the principle of equifinality.

In sum, these results underscore the configurational nature of effective livestream selling: no single step is universally most important; instead, different combinations of content volume across the four steps can lead to high sales through complementary or substitutive pathways. These insights reaffirm the need for a holistic approach that considers the selling process as an integrated system rather than a sequence of independent stages.

Finally, regarding the relative explanatory power of the three high-sales configurations, we examine their raw and unique coverage. Configurations 1a (raw coverage = 0.24; unique coverage = 0.11) and 1c (raw coverage = 0.29; unique coverage = 0.16) exhibit higher raw and unique coverage compared to configuration 1b (raw coverage = 0.17; unique coverage = 0.05). These coverage values reflect the proportion of the outcome ("high product sales") explained by each configuration, as is standard in fsQCA interpretation (Ragin, 2008b). Importantly, fsQCA does not test for statistical significance in the differences between configurations—rather, it evaluates whether each configuration constitutes a sufficient pathway to the outcome, and how much of the outcome each explains. In this sense, the relatively higher coverage of Configuration 1c suggests that a strategy emphasizing equivalence reciprocity (via the presentation step) alone accounts for a larger share of high-sales cases than configurations emphasizing overcoming objections. However, this does not imply statistical dominance but rather highlights that equivalence reciprocity may play a particularly central role in driving sales performance for snack products within the observed sample.

3.5 Robustness test

Referring to previous research, we adopted two methods to test the robustness: adjusting the frequency threshold and calibration threshold.

First, we increased the frequency threshold to 6, retaining 83% of the original cases, in line with Ong and Johnson's (2021) recommendation to maintain at least 80% of cases. The fsQCA results (Table 8) identified configurations 3a and 3b as sufficient for high product sales, both representing subsets of configurations 1a, 1b, and 1c. This supports the robustness of our initial findings. Notably, configuration 1b did not emerge under this adjustment, suggesting that overcoming objections has a weaker effect on product sales than the stronger influence of presentation, consistent with our earlier conclusions.

Table 8. FsQCA results of the Robustness Test by Changing the Frequency Threshold

	Product sales		
	High		Low
Selling step conditions	Con3a	Con3b	Con4
Approach	⊗	●	●
Presentation	●	●	●
Overcoming objections	•	⊗	⊗
Close sales	⊗	●	⊗
Consistency	0.82	0.80	0.82
Raw coverage	0.29	0.24	0.32
Unique coverage	0.17	0.13	0.32
Solution coverage	0.41		0.32
Solution consistency	0.80		0.82

Notes: "Con" indicates "Configuration". ● indicates the presence of core condition; ⊗ indicates the absence of core condition; • indicates the presence of peripheral condition; ⊗ indicates the absence of peripheral condition.

Second, we recalibrated the data using the 90th, 50th, and 10th percentiles as thresholds, as recommended by Fiss (2011) for the direct calibration method. The results based on these thresholds (Table 9) remain largely consistent with the earlier analyses. Configuration 5b replicates the initial fsQCA findings, while configuration 5a—although newly identified—highlights high content volume in both presentation and overcoming objections and low content in approach, closely resembling configuration 1c in emphasizing equivalence reciprocity. Importantly, configuration 1b does not appear in this calibration, reinforcing the conclusion that presentation has a stronger impact on product sales than overcoming objections.

Table 9. FsQCA Results of the Robustness Test by Changing the Calibration Threshold

	Product sales		
	High		**Low**
Selling step conditions	**Con5a**	**Con5b**	**Con6**
Approach	⊗	●	●
Presentation	●	●	●
Overcoming objections	●	⊗	⊗
Close sales		●	⊗
Consistency	0.83	0.87	0.82
Raw coverage	0.44	0.26	0.32
Unique coverage	0.24	0.06	0.32
Solution coverage	0.50		0.32
Solution consistency	0.82		0.82

Notes: "Con" indicates "Configuration". ● indicates the presence of core condition; ⊗ indicates the absence of core condition; • indicates the presence of peripheral condition; ⊗ indicates the absence of peripheral condition; blank space indicates "don't care" condition.

3.6 Comparing fsQCA with Latent Profile Analysis

Latent Profile Analysis (LPA) enables researchers to identify unobserved subgroups within a sample by modeling heterogeneity in the relationships among constructs (Meyer & Morin, 2016; Morin et al., 2016; Spurk et al., 2020). Both fsQCA and LPA are person-centered approaches that examine how sets of related constructs combine to influence outcomes (Gabriel et al., 2018; Wang & Hanges, 2011). Prior research has directly compared these methods, highlighting their respective strengths and similarities (Gabriel et al., 2018). In line with this, we conducted LPA to provide a methodological benchmark for fsQCA.

Given that categorizing the ten topics into four selling steps may overlook other meaningful latent structures in the data, we first performed LPA using the product-level proportional distributions across the ten topics. Analyses were conducted in R Studio (version 4.5.1). We estimated models starting with one profile and incrementally increased the number of profiles until model fit ceased to improve. Model selection was based on the Akaike information criterion (AIC) and the Bayesian information criterion (BIC), with lower values indicating better fit, along with entropy, which reflects classification accuracy (ranging from 0.00 to 1.00; values closer to 1.00 indicate higher accuracy; Jung & Wickrama, 2008). The results supported a one-profile solution as the best fit for the data (see Table 10), suggesting limited heterogeneity among the 104 products in their topic distributions.

This absence of distinct profiles may be partly attributable to sample size limitations. Previous studies suggest that LPA often requires samples of around 500 to reliably detect subtle or low-separation profiles (Spurk et al., 2020). Our sample of 104 products may thus lack the statistical power to uncover finer-grained latent classes.

Table 10. Fit Statistics for Profile Structures (10 Topics)

Number of profiles	AIC	BIC	Entropy
1	-6847.370	**-6675.485**	**1.000**
2	-6840.127	-6639.153	0.819
3	-6835.563	-6605.501	0.742
4	-6883.252	-6624.102	0.926
5	-6875.954	-6587.716	0.883
6	-6879.878	-6562.551	0.912
7	-6879.921	-6533.506	0.920
8	-6878.800	-6503.297	0.933
9	-6874.083	-6469.491	0.926
10	-6874.464	-6440.783	0.938

Notes: AIC, BIC, and Entropy are the statistics to determine model fit. AIC = Akaike information criterion; BIC = Bayesian information criterion.

To facilitate a more direct comparison with the fsQCA, which used the four selling steps as conditions, we conducted a second LPA using the proportional distributions across these steps. Again, we estimated models with an increasing number of profiles. Fit indices consistently favored a one-profile solution (see Table 11), reinforcing the conclusion that the current sample size may be insufficient for detecting meaningful subgroups with LPA.

Table 11. Fit Statistics for Profile Structures (4 Selling Steps)

Number of profiles	AIC	BIC	Entropy
1	-3923.137	**-3886.115**	**1.000**
2	-3920.826	-3870.582	0.749
3	-3920.428	-3856.963	0.799
4	-3941.470	-3864.783	0.859
5	-3946.948	-3857.039	0.878
6	-3940.460	-3837.329	0.877
7	-3952.973	-3836.620	0.900
8	-3952.764	-3823.189	0.892
9	-3943.325	-3800.528	0.860
10	-3939.856	-3783.837	0.883

Notes: AIC, BIC, and Entropy are the statistics to determine model fit. AIC = Akaike information criterion; BIC = Bayesian information criterion.

In summary, while LPA provides a valuable statistical benchmark, its reliance on larger sample sizes to detect underlying heterogeneity limited its utility in our study. The consistent one-profile solutions across both topic- and step-level analyses suggest that our sample of 104 products may lack the statistical power required for LPA to identify distinct latent profiles. In contrast, fsQCA is particularly well-suited for studies with small-to-medium samples (Fiss, 2007; Ragin, 2008). Its set-theoretic approach proved more sensitive in capturing the combinatorial effects of how different allocations of speaking time across selling steps converge to influence sales performance. Therefore, for the purpose of examining configurational pathways in a context where sample size is constrained but theoretical expectations for conjunctural causation are strong, fsQCA offers a more appropriate and insightful analytical framework.

4. Discussion

4.1 Summary

Livestreaming commerce has become a critical sales channel in the digital era (Chevalier, 2021). Its technology-driven nature makes the entire exchange process traceable and generates abundant structured and unstructured data, offering unique opportunities to examine communication-related factors (Fischer et al., 2022; Mullins & Agnihotri, 2022). This research aims to help companies design more effective livestreaming scripts by focusing on the allocation of content volume across the four selling steps to better meet consumer needs and boost purchases. Grounded in the social exchange theory and complexity theory, we investigated how the configuration of content volume across approach, presentation, overcoming objections, and close sales affects snack product sales in livestreaming commerce. The fsQCA results identify three distinct configurations that are sufficient to drive high product sales, as well as one configuration that is sufficient for low product sales.

Configuration 1a indicates that allocating high content volume to approach, presentation, and close sales (core conditions), combined with low content in overcoming objections (peripheral condition), is effective for high product sales. This configuration reflects a hybrid of transaction- and relationship-oriented strategies: presentation aligns with transactional approaches, while approach and close sales reflect relationship-building efforts. This finding aligns with research showing that both strategies can coexist (Pillai & Sharma, 2003).

Configuration 1b emphasizes high content in approach, overcoming objections, and close sales (core conditions), with less emphasis on presentation (peripheral condition). This underscores the importance of addressing consumer needs through relationship-oriented behaviors, with the salesperson acting as a “partner” who listens, responds, and fulfills customer expectations (Habel et al., 2021; Miao & Wang, 2016; Saxe & Weitz, 1982; Weitz & Bradford, 1999).

Configuration 1c shows that streamers can achieve high sales by focusing on presentation (core condition) while reducing content in approach and close sales (core conditions). This challenges the assumption that approach and presentation are always complementary, highlighting instead the strong effect of presentation combined with the weaker role of overcoming objections (peripheral condition). Theoretically, we argue that presentation and overcoming objections trigger equivalence reciprocity, whereas approach reflects goodwill reciprocity. This suggests that equivalence reciprocity alone may suffice in promoting exchanges for snack products without requiring goodwill reciprocity. Notably, Configuration 1c exhibits the highest raw and unique coverage, underscoring presentation as the most influential step. This aligns with findings that personal communication is less critical for convenience goods compared to durable goods (Finn & Kayandé, 1997) and supports the transactional orientation often observed in B2C contexts (Goad & Jaramillo, 2014; Saxe & Weitz, 1982; Verbeke et al., 2011). At the same time, it invites reflection on the ongoing shift from transaction- to relationship-oriented strategies in digital sales (Arli et al., 2018; Sheth & Parvatiyar, 1995; Verma et al., 2016).

Configuration 2 identifies a misaligned allocation—characterized by high content in approach (peripheral condition) but low content in close sales (core condition)—that is sufficient for low product sales. This highlights the critical need for alignment between the approach and close sales steps. Overinvesting in engaging consumers at the beginning without adequately closing the sale can undermine overall effectiveness. This misalignment reflects a failure to convert goodwill reciprocity established during the approach step into an actual transaction, emphasizing the importance of balancing relationship building and transaction completion.

Overall, our findings highlight the importance of strategically aligning content volume across the four selling steps to achieve high product sales in livestreaming commerce. The three high-sales configurations demonstrate that streamers can adopt different, yet effective, approaches: combining relationship- and transaction-oriented strategies (1a), focusing primarily on relationship-building behaviors (1b), or prioritizing a transaction-oriented presentation with minimal relationship cues (1c). These viable pathways reflect the flexibility streamers have in balancing goodwill and equivalence reciprocity, depending on their strengths and consumer expectations. In contrast, Configuration 2 reveals the risk of misalignment, overemphasizing the approach without sufficient close sales efforts, leading to low product sales. Together, these results underscore that approach and close sales content should be coordinated rather than decoupled, and that presentation remains a critical driver of sales outcomes. Thus, livestreaming success depends not only on the total content volume but also on its balanced and coherent distribution across the selling steps, aligning relationship-building efforts with effective transactional closure.

4.2 Theoretical contributions

This research offers several important theoretical contributions to the literature on livestreaming commerce, salesperson communication effectiveness, and implications for market maturity. First, it extends research on livestreaming commerce by addressing the underexplored role of streamer communication effectiveness. While prior studies have investigated various factors influencing livestreaming performance (e.g., Bharadwaj et al., 2022; Cai & Wohn, 2019; Chen et al., 2019), few have focused on how streamers communicate to influence sales outcomes. In particular, existing research on streamer communication has emphasized strategies or styles (e.g., Wongkitrungrueng et al., 2020) while overlooking the content and its allocation throughout the selling process. By conceptualizing communication content as comprising four standardized selling steps and examining its content volume, a neglected yet crucial dimension given the time constraints of livestreaming, this research provides a nuanced understanding of how the streamer's spoken content volume of the four selling steps jointly impacts the product sales.

Second, this research advances the salesperson communication effectiveness literature by theorizing and empirically testing the configurational effect of communication content volume across selling steps. As the foundational element of salesperson communication, research communication content primarily examined what to say (e.g., content categories, sentiment, thinking styles), while largely overlooking how much to say (Bharadwaj et al., 2017; Pennebaker, 2013; Singh et al., 2018). A few recent studies in social media contexts have shown that message length (content volume) influences engagement metrics such as likes and comments (Cuevas-Molano et al., 2021, 2022; De Vries et al., 2012; Sabate et al., 2014), but these findings are confined to asynchronous, text-based settings. In contrast, livestreaming commerce requires streamers to deliver spoken content in real time, completing the full selling process under tight time constraints. This unique, interactive context highlights the theoretical and managerial importance of understanding how content volume is distributed across selling steps. By applying fsQCA and drawing on complexity theory, this research uncovers multiple viable configurations that balance complementarity and substitution among selling steps to achieve high sales, thereby extending communication effectiveness theory to a synchronous, time-constrained retailing context and responding to calls for more configurational approaches in marketing research (Diwanji, 2023; Minerbo et al., 2021; Olya et al., 2022; Pappas & Woodside, 2021).

Third, this study contributes to the literature on market evolution and organizational learning by demonstrating how configurational methods can diagnose the maturity of emerging markets and illuminate learning directions within them. By leveraging the principle of causal asymmetry inherent in fsQCA (Fiss, 2007; Ragin, 2000, 2008b), our study moves beyond merely identifying effective patterns to precisely pinpoint a recipe for failure. The coexistence of multiple effective configurations alongside a clearly ineffective one provides a nuanced snapshot of a market in a middle stage of maturation. We contribute a novel methodological framework for theorizing about market evolution, where the identification of ineffective configurations serves as a direction for influencer learning and a catalyst for accelerated market refinement.

4.3 Practical implications

This research offers actionable implications for managers designing and optimizing livestreaming commerce strategies. First, our findings underscore the importance of thoughtful allocation of content volume across the four selling steps when designing livestreaming scripts. While firms increasingly use scripts to improve professionalism and engagement (Dixon, 2021; Katie, 2022), they often focus only on the sequence of steps rather than how much time and content to devote to each. Given the tight time constraints of livestreaming, especially in product-dense sessions, our findings show that such allocation decisions significantly affect sales outcomes. For example, allocating too much time to welcoming viewers (approach) may leave insufficient time for a compelling presentation or answering questions. Thus, marketers should design livestreaming scripts that strategically distribute content volume among the selling steps to create persuasive and time-efficient sales communication.

Second, the findings reveal a substitutional relationship between the presentation and overcoming objections steps, suggesting that streamers do not always need to excel at both detailed presentations and exhaustive overcoming objections. Prioritizing one while minimizing the other proves equally effective for sales performance. In reality, some streamers are more charismatic product storytellers who captivate audiences with vivid demonstrations and persuasive narratives, while others are better at interacting with viewers and patiently resolving doubts or concerns. Marketers should evaluate their streamers' skills and audience preferences to craft a script that plays to these strengths—for example, favoring an extended product demo for snack items with strong sensory appeal, or a more Q&A-heavy approach for high-involvement products like electronics.

Third, our findings highlight that for products such as snacks, focusing on a strong, detailed presentation can deliver superior results even when time allocated to approach or close sales is limited. This aligns with the reality that B2C audiences in livestreaming often expect quick, clear, and persuasive demonstrations of product value, rather than prolonged relationship-building (Goad & Jaramillo, 2014; Saxe & Weitz, 1982; Verbeke et al., 2011). Managers should therefore ensure that product demos are polished, visually engaging, and focused on key benefits, investing in training and rehearsals to make the presentation segment as impactful as possible.

Fourth, our findings emphasize the need for alignment between the approach and the close sales steps, indicating that mismatched emphasis—such as a warm, elaborate opening but a rushed, weak closing—can hurt sales. In practice, streamers who spend time welcoming viewers and building rapport at the beginning should also take care to "close the loop" with an equally strong, confident call-to-action at the end. This ensures consistency in tone and maintains the goodwill created during the approach step. Marketers should coach streamers on using aligned language and pacing between the opening and closing, which can reinforce the sense of professionalism and increase purchase conversions.

4.4 Limitations and future research

While this research makes significant contributions, it also has some limitations. First, this research focuses specifically on snack products, as livestreaming commerce has become an important channel for promoting and selling snacks to consumers who value convenience and variety (Chevalier, 2021). By examining snack products, we address the question of how different configurations of the content volume of the selling steps contribute to high product sales. This focus, however, also limits the generalizability of our findings to other product types. Future research could extend this configurational approach to other product categories in livestreaming commerce, such as apparel and skincare products, to examine whether the effective configurations (i.e., those associated with high product sales) differ across product types. Such comparisons would provide valuable insights into how selling strategies might be adapted to the characteristics of different products.

Second, our research did not use the 10 topics identified by the LDA model directly as conditions for the configurational analysis due to the limited sample size, which would have resulted in a high risk of limited diversity and unreliable configurations (Rihoux & Ragin, 2009). Instead, we classified the 10 topics into the four selling steps to conduct configurational analysis. While this approach offers a theoretically grounded framework, it may also obscure some finer-grained patterns inherent in the original topic structure. Future research could address this limitation by collecting a larger dataset and using the full set of LDA-generated topics as conditions in the configurational analysis. Such an approach would allow for a more nuanced examination of the underlying configurations and could reveal alternative or additional patterns beyond those captured by the four-step framework.

Third, our research focuses exclusively on what the seller says, emphasizing the content and its volume during different stages of the selling process. However, how the seller says it, including paralinguistic factors such as tone, pitch, loudness, and speech rate, also plays a critical role in shaping consumer perceptions and influencing purchase decisions (Bharadwaj & Shipley, 2020; Peterson et al., 1995; Williams et al., 1990). These delivery-related cues may amplify or diminish the effectiveness of the content itself by signaling enthusiasm, professionalism, or authenticity to the audience. Future research could integrate advanced speech analysis techniques to capture these nuanced communication dynamics and examine how they interact with content volume and structure. Moreover, leveraging multimodal data, such as voice, facial expressions, and gestures, could offer a richer understanding of the overall communication effectiveness in livestreaming contexts.

Fourth, this research faces several methodological limitations that also present opportunities for future research. Although we employed EFA as a benchmark to validate the grouping of ten topics into broader categories, the result—a single-factor solution—contrasts with the practical distinctions observed among the topics. This divergence may be attributable to our sample size, which could have limited the ability of EFA to detect a more nuanced factor structure. Similarly, when using LPA as a statistical benchmark for fsQCA, both the ten-topic and the four-step models consistently supported a one-profile solution. This is likely due to the well-documented sample size requirements of LPA, which often exceed our current dataset (Spurk et al., 2020). Future research with larger samples could re-examine these methodological benchmarks to determine whether more differentiated structures or profiles emerge. Furthermore, while fsQCA effectively identified three distinct configurations leading to high sales, an inherent limitation of the method is its inability to statistically compare the effect sizes of these solutions on the outcome. Future studies could explore hybrid approaches, for instance, by using the distinct solution classes derived from a well-fitting LPA model as grouping variables in ANOVA or regression analyses, to quantitatively compare the performance differences between various effective pathways (Gabriel et al., 2018).

Acknowledgement

We are grateful to the Editor-in-Chief, the associate editor, the editorial team, and the anonymous reviewers for their insightful comments, constructive suggestions, and editorial assistance, which significantly improved the quality of this manuscript. This work was supported by the National Natural Science Foundation of China (grant#: 72232003, 72102082; 72102223) and the Major Project in Philosophy and Social Science of Jiangsu Provincial Colleges and Universities (grant#: 2021SJZDA135).

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APPENDIX

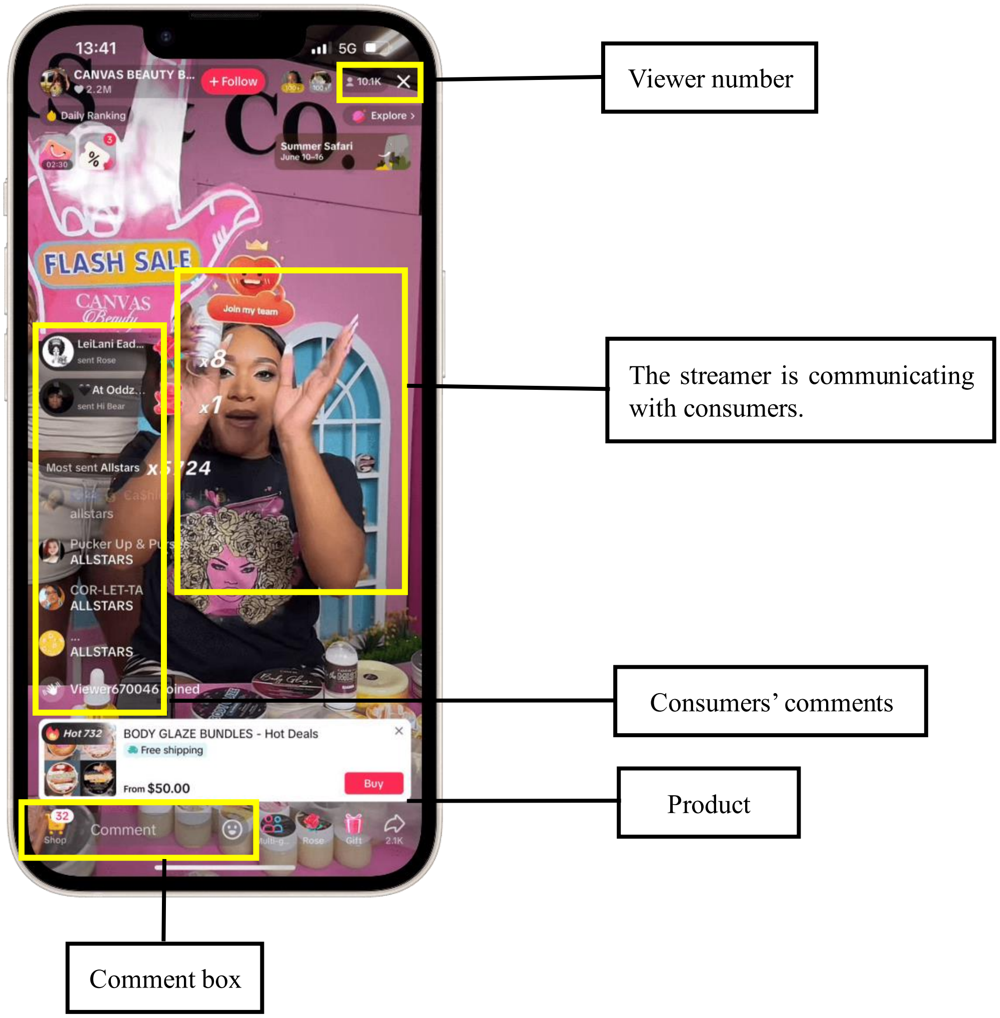

Figure 1. An example of a mobile version livestreaming commerce
(Source: https://cdn.marketplacepulse.com/articles/664/tiktok-shop-live-iamstormisteele.png)

Notes: During the livestreaming, consumers have the opportunity to input questions or comments into the "Comment box." Streamers can view and respond to these comments (see the "Consumers' comments" in Figure 1), addressing queries and actively engaging with the audience. The "Product lists" section contains products that have already been introduced, as well as those currently being discussed.