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Mapping Digital Conversation Networks of Collector Communities on Platform X: A Study of Blind Box Product Information Diffusion

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Abstract. The blind box phenomenon has created a complex digital conversation ecosystem on Platform X (formerly Twitter), where collector communities exchange information, unboxing experiences, and social validation. This study maps the digital conversation network structure of blind box collector communities on Platform X and traces product information diffusion patterns within it. Data were collected via the SocialX platform using the keywords "blind box" AND ("collector" OR "collection" OR "unboxing" OR "trading"), yielding 995 tweets from 716 unique accounts (January 15 to June 14, 2026), predominantly in English (77.8%) and Indonesian (11.3%). Five analytical methods were integrated: Social Network Analysis (SNA), Dynamic Network Analysis, Trend Analysis, Sentiment Analysis, and Text Network Analysis. The findings reveal a highly fragmented mention network divided into numerous small isolated clusters with content-resharing accounts (such as @youtube) and niche marketplace accounts (such as @chimpershq) emerging as the two dominant hubs. Dynamic network analysis confirmed that both hubs persisted consistently over time, indicating centralized information diffusion concentrated among a small number of actors. Trend analysis identified 11 conversation spikes concentrated in January to February 2026, followed by a significant decline in March to April, before recovering in June 2026. Sentiment analysis showed that community conversations were dominated by positive sentiment (42.71%), followed by neutral (37.59%) and negative (19.70%). Text network analysis revealed that unboxing, collection, series, and secret were the central concepts organizing community discourse. These findings contribute empirically to understanding how niche collector communities form and disseminate information on social media, while offering practical implications for digital marketing strategies targeting collectible product communities.

Keywords: Social Network Analysis, Blind Box, Information Diffusion, Collector Community, X (Twitter)

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1 Introduction

The growth of the blind box collectible toy industry has stimulated a significant new consumption culture worldwide, including in Southeast Asia (Wu, 2024). Blind boxes are toys packaged in sealed boxes whose character designs cannot be identified before opening (Xia et al., 2025). This design taps into a well-documented psychological principle rooted in the mechanics of gambling, where the uncertainty of the reward paradoxically strengthens the motivation to keep purchasing, as the anticipation of a potential prize sustains engagement more powerfully than a guaranteed outcome would (Xia et al., 2025; Zhang et al., 2022). Driven by this psychological appeal, the blind box industry has evolved into a global market phenomenon valued at an estimated USD 13.53 billion in 2024, projected to grow at a Compound Annual Growth Rate (CAGR) of 6.14% to reach USD 25.14 billion by 2034 (Zion Market Research, 2026). Companies such as Pop Mart, MINISO, and Sonny Angel leverage surprise, exclusivity, and product scarcity as core marketing strategies to stimulate strong collecting impulses among consumers (Barton et al., 2022). Pop Mart alone recorded extraordinary growth in the 2025 fiscal year, generating revenues of RMB 37.12 billion, representing a 184.7% increase year-on-year, while operating 630 stores across 20 countries and delivering its products to consumers in nearly 100 countries and regions worldwide including the Southeast Asian region (Pop Mart International Group Limited, 2026). In this context, collector communities play an increasingly critical role as social ecosystems that facilitate information exchange, social validation, and the construction of cultural identity around these products (Cruz et al., 2025). However, a gap persists between the idealized understanding of how these communities operate digitally and the empirical reality on the ground, particularly regarding how information about blind box products is generated, circulated, and forms complex conversation networks on social media platforms (Diana & Muhammad Haldy, 2025). Platform X (formerly Twitter) has become one of the primary spaces for these collector communities to share unboxing experiences, product release information, and to build collective identity as part of participatory digital culture (Whyke et al., 2023; Wirakusuma & Wenerda, 2023). Collectors no longer simply consume products in isolation, they produce content, share reactions, and judge one another's collections in real time with those exchanges now shaping community norms, product desirability, and the broader visibility of blind box culture in digital spaces (Rava, 2023).

Research on digital communities and information dissemination on social media has grown substantially, offering increasingly sophisticated tools for understanding how conversations form, spread, and influence behavior online (Djunaidi, 2025; Jasim et al., 2024). Studies applying Social Network Analysis (SNA) to Twitter/X have demonstrated that conversation network structures reflect clear influence hierarchies in which a small number of central actors function as dominant information bridges, measurable through metrics such as degree centrality, betweenness centrality, and closeness centrality of key nodes in the network (Srivastava & Manju, 2024). Information diffusion patterns on social media are heavily shaped by homophily in interaction networks and information distortion that favors like-minded users which structur-

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ally supports the formation of echo chambers (Cinelli et al., 2021). On the consumer behavior side, studies of collectible product marketing have shown that perceived scarcity and product exclusivity significantly influence purchase intention and information-sharing behavior among consumers (Barton et al., 2022; Hamilton & Shaheen Hosany, 2023). Furthermore, research in brand community theory has highlighted that online brand communities do not solely function as spaces for transactional information exchange, but also serve as sites of identity formation, social legitimacy, and collective value co-creation (Chapman & Dilmperi, 2022). The literature on unboxing content has similarly demonstrated that unboxing videos and posts have a significant mediating effect between product characteristics and purchase decisions, particularly through hedonic and authenticity dimensions (Vaudrey, 2022). With respect to community identification in digital networks, recent studies have shown that community detection algorithms can efficiently identify sub-communities in large-scale social media conversation graphs through modularity optimization (Kanavos et al., 2022). Sentiment analysis in social media communities has also advanced substantially, leveraging Natural Language Processing (NLP) and machine learning approaches to understand polarity and dominant discussion topics within community conversations (Wankhade et al., 2022).

Despite these advances, several knowledge gaps remain underexplored in the existing literature. First, the majority of SNA studies on Platform X have focused on political, health, or general viral topics while niche communities based on collecting interests, particularly blind box communities have received limited systematic scholarly attention (Rueger et al., 2023). Second, prior studies examining collector community behavior have predominantly relied on surveys or laboratory experiments, methods whose capacity to capture the organic, real-time dynamics of social media conversation networks is inherently constrained (Rueger et al., 2023). Third, the temporal dynamics of how blind box conversation network structures evolve over time have rarely been examined, leaving the understanding of information diffusion dynamics within these communities largely underdeveloped (Huang, 2024). Fourth, the integration of static network analysis, dynamic network analysis, and content analysis within a coherent research framework for understanding digital collector community ecosystems remains largely absent from the literature (Guédé, 2023; Hickey et al., 2025; Zhang et al., 2022).

It is worth clarifying that the contribution of this study is not simply the transfer of established SNA techniques to a new empirical context. Rather its theoretical contribution lies in showing that niche, product-centered collector communities generate a structurally distinct diffusion pattern, namely fragmented ego-networks anchored by persistent local hubs, that departs from the large-component, hierarchically bridged structures typically reported for political, health, or other viral topics. By demonstrating this divergence, the study extends the applicability of Social Network Theory and Rogers' Diffusion of Innovations to a class of online communities whose interaction logic is transactional and peer-based rather than broadcast-based, offering a boundary condition that prior SNA research on mainstream topics has not articulated.

This study offers contributions on several fronts. Methodologically, it integrates static and dynamic SNA with sentiment analysis, temporal trend analysis, and text

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network analysis within a coherent framework to comprehensively map the conversation ecosystem of the blind box collector community on Platform X (Rueger et al., 2023). Beyond methodology, the study introduces a dynamic network analysis approach to observe how the conversation network structure evolves over time, an analytical dimension that goes beyond conventional static network mapping and directly captures the information diffusion process that forms the core focus of this study (Pena et al., 2025). This study employs Social Network Theory as the primary interpretive framework for understanding the structural roles of key actors in the network, combined with Rogers' Diffusion of Innovations theory to explain the mechanisms by which information spreads over time within the community (Gondal, 2023).

Based on the background and knowledge gaps identified above, this study aims to comprehensively map the structure of the digital conversation network among blind box collector communities on Platform X, to identify key actors functioning as network hubs, to trace how information diffusion patterns develop over time, and to identify the dominant sentiments and themes characterizing community conversations (Błocki et al., 2025; Rueger et al., 2023; Whyke et al., 2023). The findings of this study are expected to contribute both to the development of digital marketing theory, particularly in understanding niche brand communities in the platform era (He et al., 2023), and to practitioners seeking to design more effective content strategies and influencer marketing approaches within digital collector community ecosystems (Leung et al., 2022). Specifically, this study is designed to address three research questions:

1. RQ1: How is the digital conversation network structure among blind box product collectors formed on Platform X and which actors play the most significant role as network hubs?
2. RQ2: How do information diffusion patterns within the blind box collector community's conversation network develop over time and during which periods does the highest conversation intensity occur?
3. RQ3: What are the dominant public sentiments and themes that emerge in blind box collector community conversations on Platform X?

2 Method

This study adopts a quantitative-computational approach with a descriptive-exploratory research design, integrating five analytical methods within a coherent framework: Social Network Analysis, Dynamic Network Analysis, Trend Analysis, Sentiment Analysis, and Text Network Analysis (Angus et al., 2023; Rueger et al., 2023). The units of analysis consist of tweets, user accounts, and mention interaction relationships within the blind box collector community conversation network on Platform X, selected for its characteristic as an open public conversation space where mention interactions can be reconstructed into a structural network (Zade et al., 2024).

Data were collected through SocialX, a social media analytics platform built on the official Platform X API (Saputra et al., 2026). The search employed a structured keyword query combining “blind box” as the primary term with secondary terms includ-

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ing "collector," "collection," "unboxing," and "trading." This data collection process yielded 995 public tweets from 716 unique accounts covering the period from January 15 to June 14, 2026 with posts predominantly in English (77.8%) and Indonesian (11.2%), reflecting the global nature of blind box discourse across diverse collector communities. The dataset includes comprehensive metadata for each tweet, including full text (full_text), creation timestamp (created_at), and mention information that forms the basis for network construction.

Two boundaries of this sampling strategy are acknowledged. First, the query combined the generic term "blind box" with generic collector-behavior terms only, and did not include brand-specific or character-specific terms such as Pop Mart, Labubu, Sonny Angel, Skullpanda, Dimoo, or Molly; conversations that referred to these products solely by brand or character name without also using the generic terms captured by the query may therefore be underrepresented, and the network, sentiment, and thematic patterns reported below should be read as characteristic of the generic-term segment of the collector ecosystem rather than the entirety of it. Second, relative to the global scale of the blind box market and the size of brand-specific communities such as Pop Mart's, the 995 tweets from 716 accounts analyzed here constitute a bounded snapshot rather than a comprehensive census of the digital conversation ecosystem, the findings are consequently best interpreted as indicative structural and thematic patterns within this bounded sample rather than as population-level estimates generalizable to the entire global collector community.

Prior to analysis, the data underwent systematic preprocessing. Duplicate tweets were removed, interaction relationships were extracted from the mentions field to reconstruct directed network edges, and text cleaning was applied through URL removal, special character stripping, and text normalization to prepare the corpus for subsequent analyses.

SNA was then applied to address RQ1 by constructing a directed graph based on mention interactions, where each node represents a user account and each edge represents a mention between accounts. Node size reflects degree centrality and colors reflect community cluster membership as detected by the community detection module within the SocialX platform (Saputra et al., 2026). It should be clarified at the outset that this network captures conversational interaction, namely who mentions or addresses whom, rather than a verified pathway of information transmission, a mention indicates conversational visibility and reach but does not by itself confirm that novel information was transmitted from one account to another. Retweet or repost networks, which more directly capture the resharing of specific content were not extracted within the scope of the SocialX mention-based data used in this study and are therefore not analyzed here. Accordingly, the term "information diffusion" is used throughout this study to describe the broader pattern of conversational visibility and reach surrounding central hub accounts, and it is used as a theoretically motivated interpretive lens grounded in Rogers' Diffusion of Innovations rather than as a direct, content-traced measure of information transmission, studies incorporating retweet or repost networks are needed to more directly measure content-level diffusion pathways. To address RQ2, Dynamic Network Analysis was applied to the same mention network using a weekly time window to observe network evolution over time (Błocki

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et al., 2025; Pena et al., 2025; Rueger et al., 2023). A weekly window was chosen because it balances sufficient interaction density per snapshot against the risk of over-smoothing short-term fluctuations, consistent with the temporal aggregation used in prior dynamic network studies of social media discourse cited above. It is acknowledged, however, that alternative temporal segmentation strategies, such as daily snapshots or rolling windows could produce different pictures of hub persistence and diffusion timing: daily windows may reveal transient bursts of local activity that are obscured within weekly aggregates, whereas monthly windows may smooth over short-lived spikes such as those subsequently identified in the Trend Analysis. The sensitivity of the reported hub-persistence findings to this choice of temporal window was not formally tested and is noted as a direction for future methodological refinement. Trend Analysis was additionally applied to the created at column to identify daily conversation volume fluctuations and spike events based on deviations from the 7-day moving average.

To address RQ3, Sentiment Analysis was applied to the full text column using a three-class model (positive, neutral, negative) provided by SocialX, with “blind box” specified as the contextual keyword to improve classification accuracy (Santhiya et al., 2021). The sentiment classifier embedded in the SocialX platform is a pre-trained multilingual model that relies on the platform's built-in language detection and a shared multilingual embedding pipeline to assign each tweet to one of the three polarity classes, rather than applying a separate model per language, this is relevant given that the corpus spans English, Indonesian, and several minority languages within the sample. This study did not conduct an independent manual validation, such as inter-rater agreement against human-coded label, of the sentiment outputs produced by SocialX. Consequently, the reported sentiment percentages should be treated as indicative of the polarity distribution generated by the platform's classifier rather than as externally validated ground truth, and future research incorporating a manually annotated subsample, particularly for non-English tweets is encouraged to assess classification accuracy more rigorously. Text Network Analysis was subsequently conducted to reconstruct term co-occurrence relationships as a weighted graph, where node size reflects term frequency and colors reflect semantic cluster membership.

All five methods were applied to an identical corpus through SocialX, ensuring direct cross-method comparability. All data used are publicly accessible via the official Platform X API, and this study applies username anonymization and uses the data exclusively for non-commercial academic purposes in accordance with the ethical guidelines of the Association of Internet Researchers (Gliniecka, 2023).

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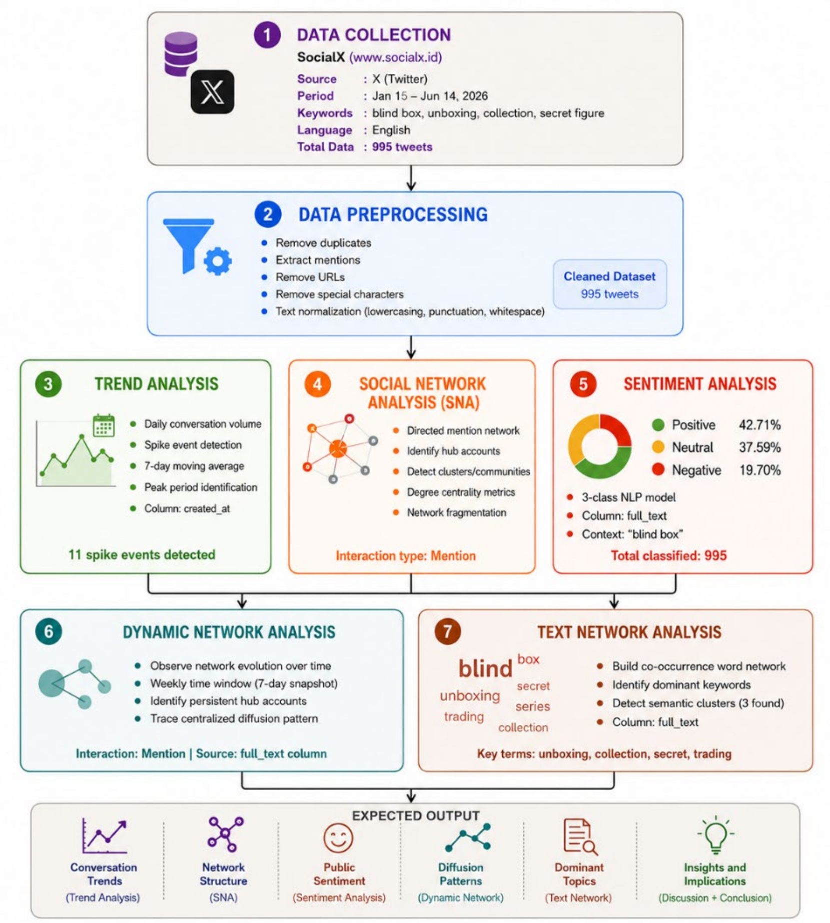

Fig. 1. Research Methodology Flow for Blind Box Collector Community on Platform X

3 Results

3.1 Dataset Characteristics

The data collection process through the SocialX platform yielded 995 English-language public tweets relevant to the blind box topic, collected throughout the period from January 15 to June 14, 2026. The entirety of these tweets constitutes a single corpus analyzed consistently through all five methods described in the Method section, enabling direct cross-method comparisons without the risk of bias arising from differences in sample size or collection period. Table 1 summarizes the main characteristics of this dataset.

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Table 1. Research Dataset Characteristics

Characteristic	Description / Value
Data source	Platform X (Twitter), via SocialX
Collection period	January 15, 2026–June 14, 2026
Total posts	995 posts
Unique accounts	716 accounts
Number of attributes	36 attributes per post
Dominant language	English: 774 posts (77.8%)
Second language	Indonesian: 112 posts (11.3%)
Verified accounts	452 posts (45.4%)
Unverified accounts	543 posts (54.6%)
Total views	5,538,777 views
Total likes	82,960 likes
Total retweets	12,770 retweets
Interaction types	Mentions, replies, retweets, quotes

Among the 716 contributing accounts, there is a fairly even distribution between verified and unverified accounts. The dominance of English (77.8%) reflects the global nature of the blind box collector community while the presence of Indonesian as the second most common language (11.3%) indicates active participation from the Indonesian collector community, a relevant finding given that Indonesia is one of the fastest-growing collectible toy markets in Southeast Asia. Other languages include French (1.4%), Japanese (1.2%), Tagalog (0.8%), and Vietnamese (0.7%), underscoring the multinational character of this community.

The total engagement figures more than 5.5 million views, over 82,000 likes, and 12,000 retweets, show that conversations about blind boxes on Platform X are not merely a marginal activity, but rather a digital discourse with significant reach and impact. On average, each post generated approximately 5,566 views, 83 likes, and 13 retweets, relatively high figures for a conversation within a niche community.

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3.2 Social Network Structure of the Blind Box Collector Community

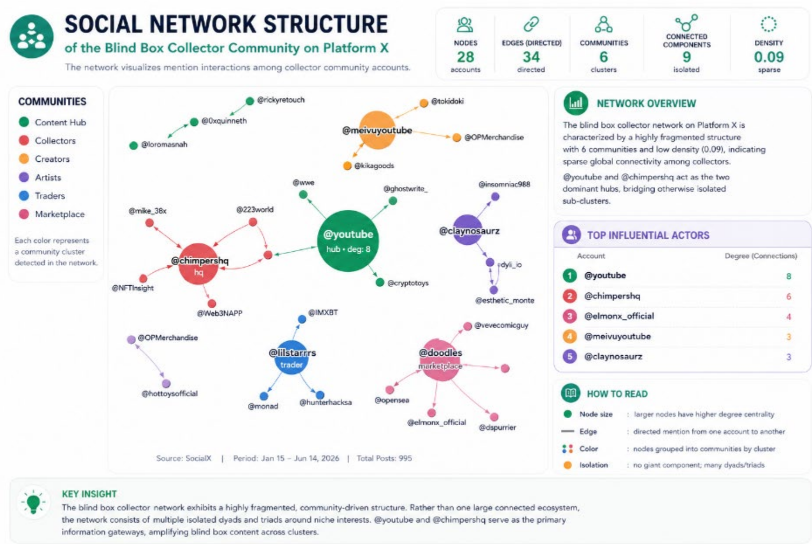

Fig. 2. Mention Network Structure of the Blind Box Collector Community on Platform X

The Social Network Analysis of the mention network among blind box collector communities revealed a highly fragmented structure. Unlike social networks in general, which typically possess a large component connecting the majority of nodes, this network decomposed into numerous small clusters isolated from one another, each consisting of only a few mutually connected accounts. Among the identifiable pairs and small groups were a cluster linking @chimpershq with @223w0rld, @mike_38x, @NFT1Insight, and @Web3NAPP; a cluster linking @doodles with @elmonx_official, @opensea, @dspurrier, and @vevecomicguy; and a cluster linking @lilstarrrs with @hunterhacksa, @monad, and @lMXBT. The account youtube appeared as the node with the largest visual size in the network, indicating the highest degree centrality, a finding that confirms that video content, most likely unboxing recordings, consistently serves as a reference cited and mentioned by collectors in their conversations on Platform X.

Two interpretive caveats are noted before proceeding. First, because the sample was bounded by a specific keyword query and a five-month collection window, part of the observed fragmentation may reflect the boundaries of data collection rather than the true underlying structure of the collector ecosystem, accounts connected through brand-specific hashtags, discussions occurring outside the sampling window, or interactions on other platforms would not appear as bridging nodes in this network, so the fragmentation reported here should be read as a property of the sampled mention network rather than a confirmed property of the collector community as a whole. Second, @youtube is not itself a blind box collector account but a general content-platform account that is frequently mentioned whenever collectors cite or link video

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content, its prominence as the largest node is therefore better interpreted as a technical artifact of cross-platform content citation than as evidence of an influential community member actively shaping collector opinion, and this distinction is maintained throughout the interpretation of hub-related findings below.

This extreme fragmentation addresses the first part of RQ1: the conversation network structure of the blind box collector community does not form as a single integrated ecosystem, but rather as a collection of dyads and small triads that largely stand independently. This pattern is consistent with the characteristics of niche communities on social media where mention interactions more frequently occur within direct peer or transactional relationships, such as between buyers and sellers, or between fans and a specific content creator, rather than in open discussions involving multiple parties simultaneously (Błocki et al., 2025; Rueger et al., 2023; Whyke et al., 2023). For the second part of RQ1, which asks which actors play the most significant role as network hubs, two accounts stand out most prominently: @youtube as the node with the largest visual representation, signifying a cross-platform content reference point, and @chimpershq as the center of the densest identifiable cluster in the network, connecting several related accounts at once. Both accounts function as information brokers at the local scale of their respective clusters, although no single account bridges the entire network globally.

3.3 Network Evolution and Information Diffusion Over Time

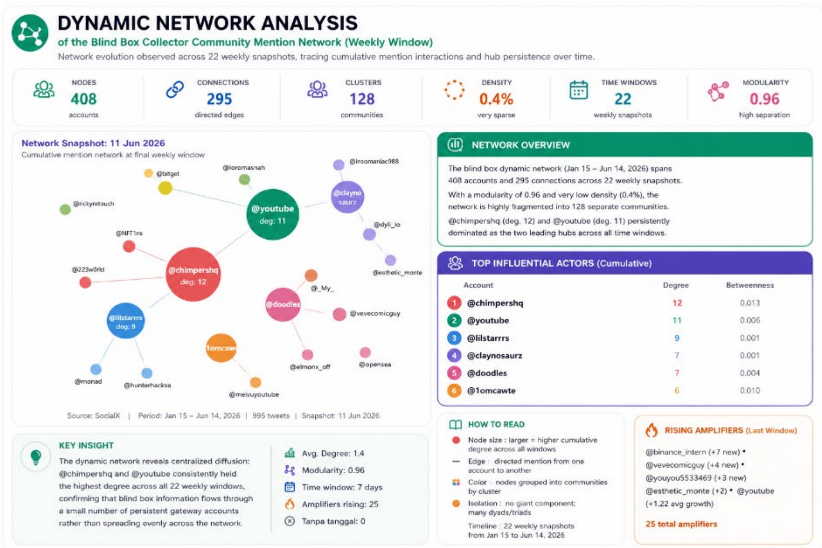

Fig. 3. Dynamic Network Analysis Results of the Blind Box Collector Community Mention Network (Weekly Window)

To address RQ2, Dynamic Network Analysis was applied to the same mention network using a weekly time window, enabling observation of network formation and

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evolution over time. The simulation snapshot at June 11, 2026 showed that @youtube and @chimpershq consistently appeared as the two nodes with the largest size, each surrounded by a number of smaller satellite nodes including @bitget, @insomniac988, @claynosaurz, @NFT1nsight, @1omcawte, and @doodles. This pattern confirms the static SNA findings while deepening the understanding of RQ2: the dominance of these two accounts is not a transient phenomenon, but a structural pattern that persists consistently throughout the weekly data accumulation.

From an information diffusion perspective, this finding indicates that the spread of information within the blind box collector community network occurs in a centralized fashion, concentrated among a small number of actors rather than dispersing evenly across many parallel pathways. When a node such as @youtube or @chimpershq receives a new mention from another account, that node functions as an accumulation point whose visibility within the network grows from week to week, rather than information spreading equally to many independent accounts. The pattern of growing satellite nodes continually clustering around the two main hubs aligns with the logic of Rogers' Diffusion of Innovations, wherein a small number of early adopters represented here by the two hub accounts, play a crucial role in introducing and maintaining the visibility of the blind box topic to a broader network, even as the overall network coverage remains fragmented. The implication is that information diffusion in this community is heavily dependent on the sustained activity of a handful of central actors, such that the withdrawal of one hub's participation could disrupt information distribution chains within the affected cluster.

3.4 Temporal Trends in Blind Box Conversations

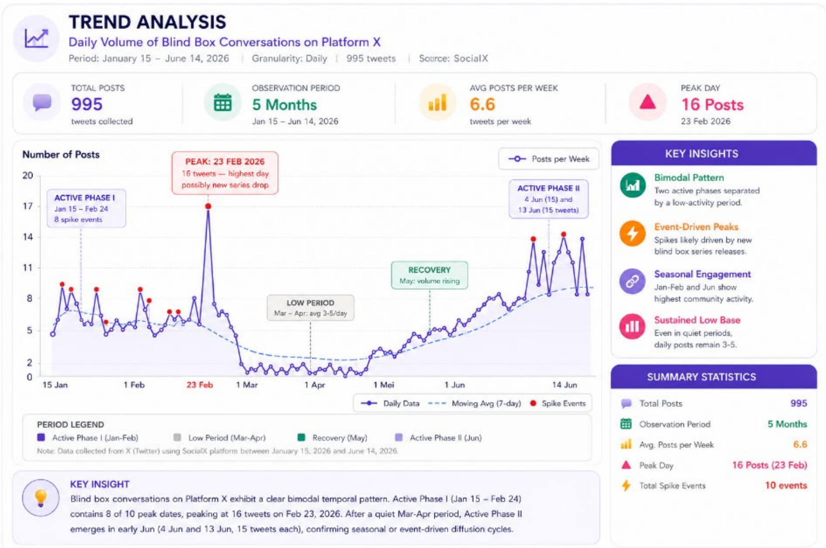

Fig. 4. Daily Volume Trend of Blind Box Conversations on Platform X (January 15 – June 14, 2026)

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Trend Analysis complements the understanding of RQ2 by presenting an aggregate picture of day-to-day fluctuations in conversation volume. Throughout the data collection period, the daily volume ranged from 0 to 15 tweets per day, with the automatic detection algorithm on the SocialX platform identifying 11 spike events, which are moments when conversation volume surged significantly above the 7-day moving average. Nine of these eleven spikes were concentrated within a six-week period between mid-January and late February 2026, while the remaining two reappeared in early to mid-June 2026, just before the end of the data collection period. Between these two active periods, throughout March to May 2026 conversation volume remained at relatively low and stable levels with no significant spikes detected.

This bimodal pattern suggests that conversation about blind box products within collector communities does not unfold uniformly over time, but is concentrated in specific periods that most likely coincide with new product series releases, promotional campaigns, or popular cultural events surrounding trending collectible characters. Returning to RQ2, these trend findings reinforce the Dynamic Network Analysis results: the January to February 2026 period when spike frequency was at its densest, was most likely also the period during which satellite nodes around @youtube and @chimpershq were most actively accumulating, such that both methods mutually reinforce each other in depicting information diffusion momentum concentrated within a specific time range, rather than dispersed evenly across the six-month observation period.

3.5 Public Sentiment toward Blind Box Products

Fig. 5. Sentiment Distribution of Blind Box Conversations on Platform X (N = 995)

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To address the first part of RQ3, Sentiment Analysis was applied to all 995 successfully classified tweets, yielding 995 sentiment data points distributed across three categories. Positive sentiment was recorded as the dominant category with a proportion of 42.71% (425 tweets), followed by neutral sentiment at 37.59% (374 tweets) and negative sentiment at 19.70% (196 tweets). This dominance of positive sentiment diverges from patterns commonly observed in large-scale social media research, which frequently finds neutral sentiment as the most dominant category owing to the high proportion of informational tweets. In conversations within the blind box collector community, affective positive expressions, most likely associated with excitement upon obtaining a particular figure, anticipation ahead of a new series release, or satisfaction with the unboxing experience, appear more frequently than purely informational statements.

Meanwhile, the non-negligible proportion of negative sentiment (19.70%) indicates that community conversations are not without friction. This negative sentiment likely stems from expressions of disappointment at receiving duplicate figures, dissatisfaction with the condition of received products, or criticism of distribution mechanisms and perceived product scarcity inequity, a pattern consistent with the intrinsic characteristics of blind box products as randomness-based products, which structurally generate satisfaction for some consumers and disappointment for others simultaneously. Overall, with positive sentiment exceeding the combined proportions of neutral and negative sentiment by a considerable margin, it can be concluded that the emotional climate surrounding blind box collector community conversations on Platform X tends to be favorable toward the product, a condition that has the potential to drive positive information dissemination through electronic word-of-mouth mechanisms.

3.6 Semantic Structure of Conversations: Text Network Analysis

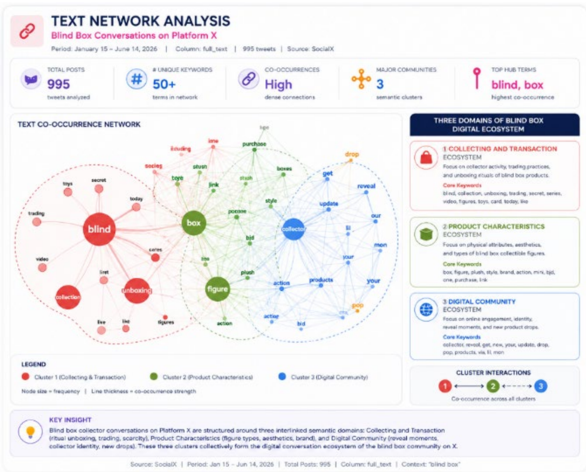

Fig. 6. Text Network Analysis of Blind Box Conversations on Platform X

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To address the second part of RQ3, Text Network Analysis was conducted to reveal the semantic structure underlying blind box collector community conversations. The analysis shows that the words “blind” and “box” appear as the two largest nodes in the network, as expected given that both are the primary search keywords. More informative are the surrounding nodes, which indicate the specific themes accompanying discussion of these products, the words “unboxing” and “collection” appear with large node sizes, signifying that the act of opening packages and the activity of collecting are the two most central and frequently discussed themes. The words “series” and “figure” also emerge as moderately large nodes, reflecting that discussions frequently reference specific release series and particular types of collectible figures.

Further, the appearance of the word “secret” closely connected to the main cluster indicates that the hidden scarcity mechanism, namely the rare secret figure that constitutes the primary incentive of the blind box product's appeal is a significant element of discourse within this conversation ecosystem. Meanwhile, the word “trading” appears as a distinct node with its own network of connections, confirming the presence of a secondary market dimension within the community, where collectors exchange or buy and sell items from their collections. The words “collector” and “reveal”, appearing in blue, also emerge as relevant nodes, reflecting the community's identity itself and the moment of unveiling the blind box contents as a performative ritual at the core of unboxing culture. The three identified color clusters (red, green, and blue) represent three overlapping thematic orientations: the red cluster, oriented toward collecting and transactional activities (collection, trading, toys, figures); the green cluster, oriented toward product characteristics (plush, style, brand, products); and the blue cluster, oriented toward digital or online moments (get, reveal, collector, new, your).

Taken together, the structure of this word network demonstrates that blind box collector community conversations on Platform X do not merely revolve around the product in a generic sense, but are organized around three distinctive elements of collector culture: the ritual of opening packages (unboxing/reveal), the scarcity mechanism (secret), and secondary market practices (trading/collection). These three elements collectively constitute the digital identity of this community on social media platforms.

3.7 Synthesis of Findings

eading all five analytical results together yields a coherent picture of the digital conversation ecosystem of the blind box collector community on Platform X. A highly fragmented network structure (SNA) yet with two consistently persistent hubs over time (Dynamic Network Analysis) indicates that information diffusion in this community is not an evenly distributed process, but one that is strongly dependent on a small number of central actors. This centralized diffusion pattern aligns with the temporal concentration found in the trend analysis wherein the majority of conversation spikes occurred within a relatively brief window at the beginning of the observation period. Meanwhile, the generally positive emotional climate (Sentiment Analysis) and the thematic structure centered on unboxing rituals, scarcity mechanisms, and trading

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practices (Text Network Analysis) provide context for why this community remains actively engaged despite its fragmented structure, community bonds appear to be built more through shared interests and collective cultural rituals than through a dense, tightly interconnected social interaction network.

4 Discussion

The findings presented above carry several theoretical and practical implications. First, from the perspective of Social Network Theory, a fragmented yet hub-consistent network structure suggests that blind box collector communities operate more as a collection of small overlapping ego-networks than as a single large, cohesive community. This differs from SNA research findings on viral or political topics which typically reveal networks with large components connecting the majority of their users. Such characteristics are consistent with the nature of special interest niche communities in which interactions tend to be personal and transactional, such as between sellers and buyers, or between fans and a specific content creator, rather than public and open to mass discussion.

Second, the finding that @youtube and @chimpershq consistently remain the two dominant hubs over time provides empirical support for Rogers' Diffusion of Innovations theory in the context of digital niche communities. Although the overall network coverage remains small and fragmented, the persistence of these hubs indicates the operation of an information gatekeeping mechanism, a small number of actors effectively control the visibility of content circulating among the existing small clusters. The practical implication is that brands or vendors of blind box products seeking to expand their information reach on Platform X need to identify and collaborate with such central actors, rather than relying on a strategy of broadcasting content indiscriminately to many independent accounts.

Third, the combination of predominantly positive sentiment with a thematic structure centered on unboxing, scarcity, and trading indicates that the appeal of blind box products to their collector communities rests on three mutually reinforcing experiential pillars: the pleasure of opening packaging, the tension arising from outcome uncertainty, and the social satisfaction derived from collection exchange activities. This pattern aligns with the literature on perceived scarcity in collectible product marketing which shows that perceived scarcity consistently intensifies consumer affective responses, manifesting as both enthusiasm and frustration.

Fourth, the temporal concentration of conversation spikes during January to February 2026 and their recurrence in June 2026 suggests that the blind box industry, like the retail sector more broadly is strongly shaped by product release cycles and calendar momentum. For business practitioners, an understanding of such seasonal patterns is relevant for determining optimal timing for new product launches or marketing campaigns to coincide with periods when the community is most actively engaged.

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5 Conclusion

This study aimed to map the digital conversation network structure of blind box collector communities on Platform X and to trace the patterns of information diffusion within it, employing a combination of Social Network Analysis, Dynamic Network Analysis, Trend Analysis, Sentiment Analysis, and Text Network Analysis applied to 995 tweets collected through the SocialX platform.

Addressing RQ1, the SNA results show that the blind box collector community's conversation network is highly fragmented, consisting of numerous small clusters that largely stand independently without a large component unifying the overall network. The accounts @youtube and @chimpershq emerged as the two actors with the highest degree of connectivity, each functioning as a local hub within their respective clusters.

Addressing RQ2, Dynamic Network Analysis confirmed that both hubs persist consistently over time, indicating that information diffusion within this network is centralized among a small number of key actors. This finding is reinforced by the Trend Analysis results which identified 11 conversation spikes with the highest concentration occurring during the January to February 2026 period.

Addressing RQ3, Sentiment Analysis revealed that community conversations are dominated by positive sentiment (42.71%), followed by neutral (37.59%) and negative (19.70%), indicating a generally favorable emotional climate toward blind box products. Text Network Analysis complemented this picture by revealing that the themes of unboxing, collection, secret, and trading constitute the central concepts linking the various aspects of community conversation.

Theoretically, this study contributes by demonstrating how niche interest-based collector communities form network patterns that differ from social media communities on viral or public topics, and by showing how the combination of static and dynamic network analysis can capture the information diffusion process more richly than a single-timepoint network analysis alone. Practically, the findings suggest that digital marketing strategies for collectible products such as blind boxes need to identify and collaborate with persistent central actors in the network while also factoring in seasonal momentum when designing product launch timing and promotional campaigns.

This study has several limitations. First, the data are limited to a single platform (X) and a single language (English), and therefore do not capture blind box collector community conversations on other platforms such as TikTok and Instagram, nor conversations in other languages such as Indonesian. Second, the network analyzed is based solely on mention interactions, meaning other interaction types such as replies and quote tweets which may yield different network structure findings have not been captured. Third, the relatively limited dataset size (995 tweets) constrains the generalizability of the findings to the global blind box collector community population. Future research is encouraged to expand platform and language coverage to compare network structures across different interaction types, and to employ longer data collection periods to validate the consistency of the seasonal patterns identified in this study.

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7 Conflict of Interest

The authors declare no financial or non-financial conflict of interest related to the research, authorship, and/or publication of this article.

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