Caught in the Craze: Understanding Consumer Engagement in the Labubu Phenomenon

A Quantitative Social Media Study Examining how Emotions, Sentiment, and Discussion Topics are Associated with Online Consumer Engagement

Authors

Alexandra Gustafsson

Nicki Lager

Supervisor

Fredrik Lange

Examiner

Alexander Mafael

Stockholm School of Economics

Retail Management Program

Abstract

Rapidly evolving digital trends have today become increasingly embedded in contemporary consumer culture. However, research has yet to fully explain which factors are associated with consumer engagement within highly viral digital trend environments. This paper extends the understanding of digital consumer behavior by investigating how discussion topics, sentiment patterns, and emotional expressions relate to consumer engagement in the Labubu phenomenon. Using Reddit as a data source, the study analyzes user-generated social media discussions through a quantitative text analysis approach combining topic modeling, sentiment analysis, and emotion detection. The results show that specific discussion topics and emotions are associated with higher levels of consumer engagement, while sentiment and emotional expressions also relate differently to engagement depending on the discussion context. We discuss several theoretical and managerial implications of these findings and contribute to a deeper understanding of consumer engagement in fast-moving digital trend environments.

Keywords: Consumer Engagement, Social Media, Viral Consumption Trends, Emotions, Sentiment Analysis, Topic Modeling, Online Communities, Digital Consumer Behavior.

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1. Introduction & Background

"But seriously what is this Labubu?"

"[...] People are lining up, even getting into fights over these toys"

"[...] Everyone has to have one now."

These reactions point to how contemporary consumption trends can escalate at an unprecedented speed. Consumers encounter products like Labubu at the same time as they witness others rushing to obtain them, creating a sense that the trend is rapidly growing in real time. In this environment, attention itself becomes contagious, allowing relatively unknown products to rapidly snowball into global consumer crazes.

1.1 Labubu as a Case

In this study, Labubu is used as a case to illustrate the acceleration of trend formation in contemporary consumer culture. Labubu refers to a small collectible designer plush-toy, often used as a bag accessory, characterized by a distinctive "cute-ugly" aesthetic with exaggerated facial features (Kim, 2025). Originally created in 2015 by Hong Kong-born artist Kasing Lung as part of an art series, Labubu was later commercialized by Pop Mart into a collectible product line. From these relatively niche origins, Labubu has rapidly transitioned into the mainstream. Its swift rise highlights how product trends can quickly gain traction in today's digital environment, evolving into both a cultural and commercial phenomenon with widespread attention and popularity (Sinha, 2025).

Figure 1. Labubu

A central factor contributing to this popularity is Labubu’s blind-box model, introduced in 2016, where consumers purchase sealed packages without knowing which figure they will receive. By combining uncertainty with collectability, the model encourages emotional investment and repeated purchasing behavior. At the same time, social media and popular culture play a central role in driving the trend. TikTok unboxings, celebrity exposure, and online communities contribute to visibility, community formation, and increased engagement around the product (Sinha, 2025). Celebrities such as Rihanna, Dua Lipa, Kim Kardashian, and Blackpink’s Lisa have further accelerated the trend by making the dolls increasingly visible across popular culture and online spaces. As the dolls became more visible, their popularity reinforced itself, reflected in online discussions where people want these dolls because they are popular, and they are popular because people want them (Di Placido, 2022; Wang & Hancock, 2025).

The scale and rapid diffusion of this trend are also reflected in Pop Mart's financial performance. By 2025, the company reported revenues exceeding RMB 37 billion, with the “Monsters” series, of which Labubu is a part, generating over RMB 14 billion alone (Pop Mart International Group, 2025, pp. 6, 27). The series quickly became central to the company’s growth, illustrating how rapidly digitally diffused consumer trends can develop into major commercial phenomena.

Overall, Labubu illustrates how contemporary consumer trends can rapidly evolve from niche products into large-scale cultural and commercial phenomena. Through continuous online visibility, the product has gained momentum far beyond its original artistic context. The case therefore highlights how digitally diffused trends are increasingly shaped not only by the product itself, but also by the attention and engagement surrounding it.

1.2 A Changing Consumer Landscape

In recent years, the consumer and fashion landscape has undergone a significant transformation in how trends emerge, spread, and gain momentum. Industry insights suggest that fashion is increasingly shaped by what has been described as a “dopamine culture,” where social media algorithms continuously promote speed, spectacle, and novelty (McKinsey & Company, 2025a). As a result, trends can rapidly gain widespread visibility while also becoming increasingly short-lived. This accelerated pace of trend cycles has also changed consumer behavior, as products can move from initial exposure to purchase consideration almost instantly. Consequently, the traditional discovery funnel has become significantly compressed, moving toward near-instantaneous decision-making (McKinsey & Company, 2025a; Boston Consulting Group [BCG], 2025).

These shifts in how trends spread and purchasing decisions are made also reflect broader changes in consumer behavior. As digital consumption has become more embedded in everyday life, consumer patterns have become increasingly difficult to predict, making traditional frameworks for understanding behavior less applicable. This shift accelerated during the COVID-19 pandemic, when consumers adopted new forms of digital engagement and online consumption almost overnight, many of which have persisted beyond the pandemic. At the same time, consumers are behaving in increasingly inconsistent ways, such as reducing spending in some areas while increasing it in others, making their decisions more difficult to anticipate (McKinsey & Company, 2025b). Together, these developments point to a consumer environment characterized by rapid behavioral change and reduced predictability in decision-making.

A central element of this evolving landscape is the growing role of digital and social platforms. As social relationships are increasingly maintained online (Al-Jbouri et al., 2024), digital platforms have become closely connected to how consumers form opinions and make decisions. Consequently, social media has become a key environment for discovering brands, finding inspiration, and digging into products they might want to buy (Walsh, n.d.; McKinsey & Company, 2025b), reflecting its growing role in product discovery and research.

Building on this, social media platforms have increasingly become central spaces where consumers evaluate products and make purchasing decisions. Platforms such as TikTok, Instagram, and YouTube now account for over 60% of product discovery, surpassing traditional search engines such as Google and highlighting a substantial shift in how consumers research and evaluate products. Rather than relying on traditional search processes, consumers increasingly use social media to discover products, read reviews, and compare alternatives before making purchasing decisions (Sprout Social, 2026).

Collectively, these developments point to a consumer environment in which digital platforms increasingly shape how consumers discover, evaluate, and engage with products. As trends spread faster and decision-making becomes more immediate and unpredictable, social media has become deeply embedded in everyday consumption processes, turning digital platforms into central spaces where trends gain momentum and consumer behavior is shaped in real time.

1.3 Research Gap & Managerial Relevance

Although previous research has established that product adoption is shaped by social influence and symbolic value creation (e.g., Fisher & Price, 1992; Bearden & Etzel, 1982; Keller, 1993), a gap still exists in the need to continuously examine the factors associated with consumer engagement within today's fast-changing and highly viral digital environment. As these trends become increasingly prominent in contemporary consumption, developing a deeper understanding of the factors related to consumer engagement becomes increasingly important. These relationships are explored further in the theory section.

For practitioners, this study is also expected to offer important implications. Given the increasing role of digital platforms in shaping consumer behavior and accelerating trend diffusion (Deloitte 2025; McKinsey & Company, 2025a), understanding what motivates consumers to engage with rapidly evolving trends has become increasingly important for managers and marketers. This is particularly relevant in fast-moving consumer markets, where many new products fail before reaching their first year due to high speed and volatility (Derqui et al., 2022). Thus, this thesis is expected to provide valuable insights for managers by identifying factors related to consumer engagement in fast-moving digital trend environments.

1.4 Purpose & Contributions

Against this background, there is a growing need to better understand the factors associated with consumer engagement within rapidly evolving digital trend environments. To address this gap, the present study investigates how different forms of online expression and interaction relate to consumer engagement in fast-moving consumption trends. More specifically, the study analyzes user-generated social media data within a single product case, Labubu. By focusing on naturally occurring digital discussions, the study seeks to identify patterns and relationships associated with engagement in contemporary social media environments.

Specifically, our study addresses the following research questions with their corresponding empirical focus (see **Table 1)**:

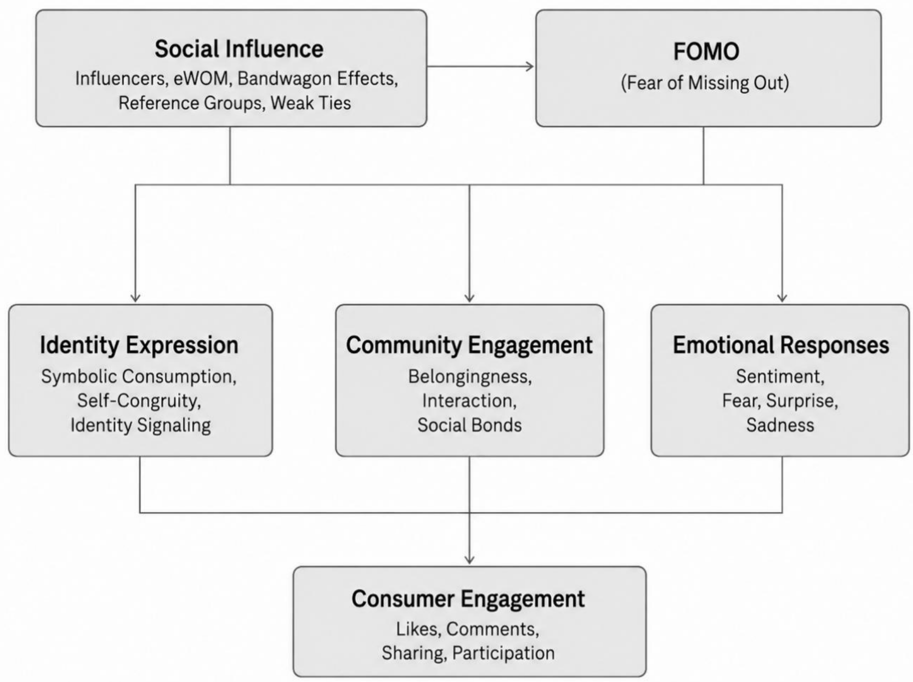
Table 1. *Research Question(s)*

Research Question(s)	Empirical Focus
RQ1. To what extent are specific discussion topics associated with higher levels of consumer engagement within the Labubu trend?	Discussion topics
RQ2. How are sentiment patterns related to consumer engagement with the Labubu phenomenon?	Sentiment
RQ3. How are emotional expressions related to consumer engagement with the Labubu phenomenon?	Emotions
RQ4. How do discussion topics moderate the relationship between sentiment and engagement?	Moderators
RQ5. How do discussion topics moderate the relationship between emotional expressions and engagement?	Moderators

2. Theory

The first section of the theory (Theoretical Background) draws on early research that has examined phenomena related to this study, thereby establishing a basis for understanding how consumer trends spread and achieve widespread adoption. While these studies provide valuable insights into the social processes underlying diffusion, they have largely been developed in pre-digital media contexts and therefore do not fully capture how such dynamics unfold in today's digital environment.

Building on this foundation, the following sections present theory deemed particularly relevant for understanding, interpreting, and contextualizing key themes identified in the empirical findings, allowing the empirical insights to guide the analysis.



Framework 1: Overview of the Theoretical Framework

2.1 Theoretical Background

The diffusion of consumer product trends cannot be understood solely in terms of functional or utilitarian needs; rather, it must be viewed as a socially constructed process. Research on adoption behavior demonstrates that the spread of new products is closely tied to the pursuit of social rewards, where adoption functions as a means of achieving social integration or differentiation within a group (Fisher & Price, 1992). This perspective shifts the analytical focus from a product's objective features to its communicational value, suggesting that trends gain momentum when they are socially visible and linked to influential reference groups.

Adoption by superordinate groups, meaning those who seek out new products as a means of establishing and communicating social differentiation, further enhances the social desirability of a product. Through a transfer of meaning from the group to the product, consumers' expectations of both social approval and personal product benefits are shaped (Fisher & Price, 1992). In line with this, Keller (1993) argues that customer-based brand equity (the value a brand holds for consumers) is influenced by perceived symbolic benefits. These benefits refer to the extrinsic advantages of consumption that satisfy underlying needs for social approval, prestige, and the expression of self-concept.

In turn, the influence of reference groups is central to understanding how products achieve widespread adoption. However, the extent of this influence depends significantly on the conspicuousness of the product. For instance, whether it is consumed in public or private. When a product is visible to others, the act of adoption becomes a signal of group affiliation. As a result, consumers become more susceptible to value-expressive influence, which is driven by the psychological need to associate with a particular person or group (Bearden & Etzel, 1982). This dynamic is further reinforced by status consumption, defined as a motivational process in which individuals seek to enhance their social standing through the consumption of products that symbolize prestige (Eastman et al., 1999).

In addition, the adoption of products is moderated by normative evaluations. These evaluations reflect a consumer's internal judgments about the appropriateness of a purchase within a specific context. Acting as a behavioral gate, normative evaluations can discourage behavior even when an individual has a strong predisposition toward it, if the action is perceived as socially unacceptable. Conversely, when a behavior is considered socially sanctioned, individuals are far more likely to act on their inherent tendencies (Rook & Fisher, 1995). This suggests that trends spread not only because of individual preferences, but because the act of adoption itself is evaluated as appropriate or desirable within a given social context.

The structural diffusion of these social processes across a population can be explained by the strength of weak ties. While strong ties (such as close friends) tend to form dense and insular networks where information is often redundant, weak ties (such as acquaintances) serve as critical bridges between otherwise disconnected groups. These bridges facilitate the flow of information and social influence across social boundaries, enabling trends to spread between network clusters that would otherwise remain isolated (Granovetter, 1973).

By synthesizing perspectives on social influence, symbolic value, status-seeking, normative evaluation, and network bridging, it becomes evident that the social construction of value is a key driver of trend diffusion. This theoretical foundation provides a solid basis for examining how products achieve widespread engagement, emphasizing that these social aspects are central to how trends spread.

2.2 The Mediating Role of FOMO in Scarcity Marketing

Product scarcity is a vital tool in marketing because it leverages the psychological tendency to value products that are difficult to obtain (Barton et al., 2022). This uncertainty in obtaining the product can evoke a fear of missing out (FOMO), which acts as a mediating mechanism between product scarcity appeals and consumers' impulse buying intentions, as scarcity triggers FOMO, which in turn promotes impulsive purchasing behavior and increases consumers' sense of urgency (Aydın, 2019; Tang et al., 2025). While scarcity cues increase the perceived risk of losing access to a desired product, FOMO reflects the psychological apprehension associated with being excluded from rewarding experiences that others may be enjoying (Przybylski et al., 2013). Within a consumption context, this has been conceptualized as "consumer-centric FOMO," referring to the fear of not acquiring a product or participating in an experience valued by others (Good & Hyman, 2020).

Such fears are further shaped by social motivations, as individuals seek to balance their sense of belonging with their sense of self. In this context, individual differences such as the need for uniqueness and consumer independence influence the extent to which consumers experience FOMO, with a stronger need for uniqueness increasing susceptibility to FOMO, while higher consumer independence reduces it. This, in turn, influences socially motivated consumption behaviors such as conformity and conspicuous consumption, with the desire for belonging increasing these behaviors (Argan et al., 2022).

2.3 Social Influence

The decision-making process of a consumer is rarely an isolated cognitive event; rather, it is deeply embedded in a social network that continuously calibrates preferences through interpersonal interaction. In particular, individuals often look to social norms and the behavior of others to form accurate judgments, especially under conditions of uncertainty (Cialdini, 2001). Consequently, individual choices are influenced by the perceived expectations and behaviors of others, leading consumers to adjust their behavior accordingly (Cialdini & Goldstein, 2004).

As products gain popularity, more consumers adopt them, reflecting a bandwagon effect in which individuals follow the behavior of the majority. This suggests that consumption behavior is shaped by social influence, as individuals imitate the actions and attitudes of others rather than relying solely on intrinsic product characteristics (Leibenstein, 1950; Bindra et al., 2022). When imitation becomes pervasive and individuals rely on the observed choices of others rather than their own information, herd behavior can emerge (Banerjee, 1992).

In digital environments, parasocial interactions further shape this process by creating an illusion of intimacy with influencers, which, according to Nadroo et al. (2024), increases perceived credibility and influences consumer attitudes and behaviors. Chen et al. (2019), position vicarious expression (i.e., consumers' indirect experience of products through others' online interactions and reviews) as a key mechanism enabling product comprehension through indirect virtual experiences, while Nadroo et al. (2024) finds that eWOM emerges as a potent social cue that rekindles the bandwagon effect, underscoring its pivotal role as a mediator in a cyclic, self-sustaining chain of consumer engagement that strongly drives consumers' intention to purchase online. These mechanisms highlight how consumer evaluations are increasingly shaped by social signals rather than purely functional product attributes. Similarly, Li et al. (2025) argue that adoption decisions are shaped not only by functional product characteristics, but also by the emotional and social value constructed through peer influence, which further affects consumers' willingness to adopt new products.

2.4 Consumer Interpretation and Meaning Construction

Consumers rarely have complete information about products, and therefore rely on inferential strategies to fill gaps in their knowledge when forming judgments and making decisions (Deval et al., 2013). These strategies are often grounded in "naive theories", informal, common-sense frameworks used to make sense of marketplace phenomena. These theories shape how consumers interpret product information, as the priming of different, sometimes contradictory, naive theories can lead to different inferences and judgments (Deval et al., 2013). This process of meaning construction goes in line with Consumer Culture Theory, which emphasizes that consumers actively rework and transform marketplace symbols to manifest their personal and social circumstances and further their identity and lifestyle goals (Arnould & Thompson, 2005).

This interpretive flexibility is not merely cognitive but also heavily influenced by social context, as consumer responses to highly innovative and atypical products exhibit a reluctance to express a preference for highly atypical products, partly driven by concerns about maintaining membership within a community. Consistent with this, the relationship between atypicality and preference is curvilinear: products with low atypicality are often perceived as uninteresting, those with moderate atypicality are most preferred, while highly atypical products tend to be rejected (Formilan et al., 2021).

2.5 Consumer Community Engagement

In contemporary consumer culture, the phenomenon surrounding a product can generate linking value, where a significant part of the value lies in the social bonds activated between users rather than solely in functional benefits (Marchowska-Raza & Rowley, 2024). These communities are frequently anchored in perceived homophily, as individuals tend to interact with and be attracted to others who share similar values, attitudes, and characteristics, which in turn fosters participation and a sense of belonging (Osei-Frimpong et al., 2022). Within brand communities, fans maintain engagement through two interrelated pathways: their identification with the focal brand and the interpersonal relationships developed with fellow members, which together shape a sustained relationship (Katz et al., 2020).

Emotional support further strengthens these social bonds, as social networking practices such as empathizing provide affective resources within a sympathetic social network and reinforce social and moral bonds among members (Schau et al., 2009). To deepen these bonds, brands can utilize openness in communication, sharing personal stories or "back-stage" details to foster a sense of intimacy and a one-to-one relationship with the consumer (Labrecque, 2014). This communicative strategy provides resources that stimulate consumer engagement, with brand communities preserving these interactions as a 'value vestige', an enduring repository of value-related discourse. This accumulated knowledge enables both active and passive participants to derive value from the continuous exchange of information, ideas, and experiences within the community (Marchowska-Raza & Rowley, 2024).

In addition to the social value created through shared interaction and knowledge exchange, communal engagement may also be driven by self-status seeking, as consumers participate to express their identity and gain respect and recognition within the community (Osei-Frimpong et al., 2022). Repeated positive interactions can contribute to the development of emotional attachment, defined as an emotion-laden bond characterized by deep feelings of connection, affection, and passion toward the brand (Kumar et al., 2019). This process can be further explained through self-categorization, whereby individuals assimilate their self-concept to a group prototype, leading to a depersonalization process in which their feelings, perceptions, and behaviors align with the norms of the group (Katz et al., 2020). When emotional connectedness is established, it fosters customer engagement, reflected in both direct and indirect contributions such as purchases, referrals, and feedback (Kumar et al., 2019).

2.6 Identity Expression and Symbolic Consumption

Symbolic Self-Completion Theory suggests that individuals use material possessions and recognizable symbols to communicate their identity to others (Wicklund & Gollwitzer, 1981). This process, referred to as identity expressiveness, reflects a brand's ability to signal both personal and social identity (Xie et al., 2015). According to the mentioned theory, materialistic consumers use acquisitions to reduce perceived self-discrepancies and move closer to a more complete version of themselves (Koksal et al., 2025). Similarly, Self-Congruity Theory proposes that consumers prefer brands that align with their actual, ideal, or social self-image (Sirgy, 1986), allowing individuals to connect brands with their self-identities (Koksal et al., 2025).

Fashion serves as a primary transmitter of values and cultural significance (Dykhnych et al., 2025). The visual aesthetics of a product are not merely decorative but function as meaningful instruments through which consumers navigate and articulate their identities (Koksal et al., 2025). Indeed, the choice of a highly aesthetic product can act as a direct form of self-affirmation, reinforcing a consumer's sense of self and core personal values. This psychological aspect of aesthetics influences behavior regardless of whether an individual admits to prioritizing design in their decision-making (Townsend & Sood, 2012).

Beyond individual expression, consumption practices are closely connected to lifestyle choices and the pursuit of social belonging (Dykhnych et al., 2025). Through identity signaling, brands enable consumers to gain social validation by aligning with desired groups while distancing themselves from undesired identities (Zhu et al., 2024). In this process, consumers' perceptions of a brand become increasingly important, as perceived quality shapes both cognitive evaluations and perceptions of social expectations. When a brand's identity aligns with a consumer's self-concept, emotional involvement and intentions to engage with the brand become stronger (Hsu et al., 2026). As a result, consumers who internalize brands as part of their identity become more likely to make spontaneous purchases that reinforce identity expression (Koksal et al., 2025).

2.7 Emotions in Consumer Behavior

The role of emotions in consumer behavior is recognized as a central factor that influences every stage of the buying process, partly through affecting consumer evaluation and behavior (Sharma et al., 2023; Aeron & Rahman, 2023). At a broad level, emotions have been explored by dividing into positive and negative sentiments. Positive emotions are generally associated with pleasant situational responses. Findings suggest that these sentiments trigger a higher buying propensity by fostering loyalty, satisfaction, and empowerment. Conversely, negative emotions often breed destructive behaviors, such as consumer complaints and the failure of value co-creation (Sharma et al., 2023).

Theories such as the “mood-as-information” model have traditionally argued that a consumer’s sentiment directly influences how they evaluate a brand. In simple terms, positive emotions usually lead to positive opinions about a brand, while negative emotions tend to create negative opinions (Forgas, 1995). However, newer research shows that this relationship is not always so straightforward and that sentiment does not automatically lead to certain behaviors (Aeron & Rahman, 2023). More recent theories, especially the “mood-as-input” model, suggest that the effect of sentiment depends on the situation and the surrounding environment (Fredrickson, 1998; Griskevicius et al., 2010; Raghunathan & Pham, 1999). To achieve higher explanatory power, literature has moved beyond simple valence to examine discrete emotions (Lerner & Keltner, 2000). Accordingly, the following sections examine the discrete emotions of sadness, surprise and fear in detail.

Firstly, sadness is associated with themes of loss, helplessness, and a lower sense of situational control (Raghunathan et al., 2006; Raghunathan & Pham, 1999; Smith & Ellsworth, 1985). As these feelings reduce individuals’ perceived control over their situation, consumers may begin to evaluate their environment more negatively. Nevertheless, sadness can motivate individuals to improve their situation or compensate for perceived feelings of loss and helplessness through different forms of behavior and consumption (Andrade, 2005; Garg et al., 2007; Raghunathan & Pham, 1999).

Further, the effects of sadness appear to depend on contextual factors. Previous research suggests that when individuals perceive their sadness as unrelated to the current decision-making situation, its influence on behavior becomes weaker (Garg et al., 2007; Raghunathan et al., 2006; Small & Verrochi, 2009). In situations where sadness does influence consumer behavior, the type of product further moderates its effects. Garg et al. (2007) found that sadness increases the consumption of hedonic products, while reducing the consumption of less hedonic products. Beyond consumption behavior, sadness has also been associated with increased tendencies to seek help from others (Aeron & Rahman, 2023).

Secondly, surprise has been shown to strongly influence consumer behavior by increasing consumers' tendency to engage in word-of-mouth communication about their experiences (Derbaix & Vanhamme, 2003). Surprising experiences interrupt consumers' normal expectations and create a "schema discrepancy", which captures attention and increases emotional intensity. As a result, consumers become more motivated to process and discuss the experience with others. Derbaix and Vanhamme (2003) further found that both positive and negative surprise increase consumers' likelihood of sharing their experiences, while stronger levels of surprise lead to more frequent word-of-mouth communication. The authors explain this through the concept of "social sharing of emotions," suggesting that emotionally disruptive experiences naturally encourage social interaction and communication.

Thirdly, fear is an emotional response to perceived threats and uncertainty (Smith & Lazarus, 1993). Because fear is associated with situational accountability, individuals often perceive the negative situation as being outside of their control (Kemper & Lazarus, 1992; Lerner & Keltner, 2000; Smith & Ellsworth, 1985). This uncertainty causes consumers to process information more carefully and systematically, which can increase avoidance behavior, also referred to as a "flight tendency" (Passyn & Sujan, 2006). Moreover, previous research has linked fear to more negative evaluations, increased affiliation-seeking behavior, reduced engagement, and lower behavioral intentions (Achar et al., 2020; Ben-Ami et al., 2014; Griskevicius et al., 2009; Wolf et al., 2021).

This tendency toward affiliation-seeking suggests that individuals may cope with fear by turning to others for social connection and reassurance (Chen & Pham, 2018). As such, consumers' existing sense of affiliation can influence how fear affects their evaluations and behavior. Dunn and Hoegg (2014) found that fear strengthens emotional attachment and positive evaluations of brands when consumers experience a low sense of affiliation, whereas this effect weakens when consumers already feel socially connected. Similarly, Griskevicius et al. (2009) showed that fearful consumers become more responsive to social proof appeals, as following others provides a sense of comfort and reassurance.

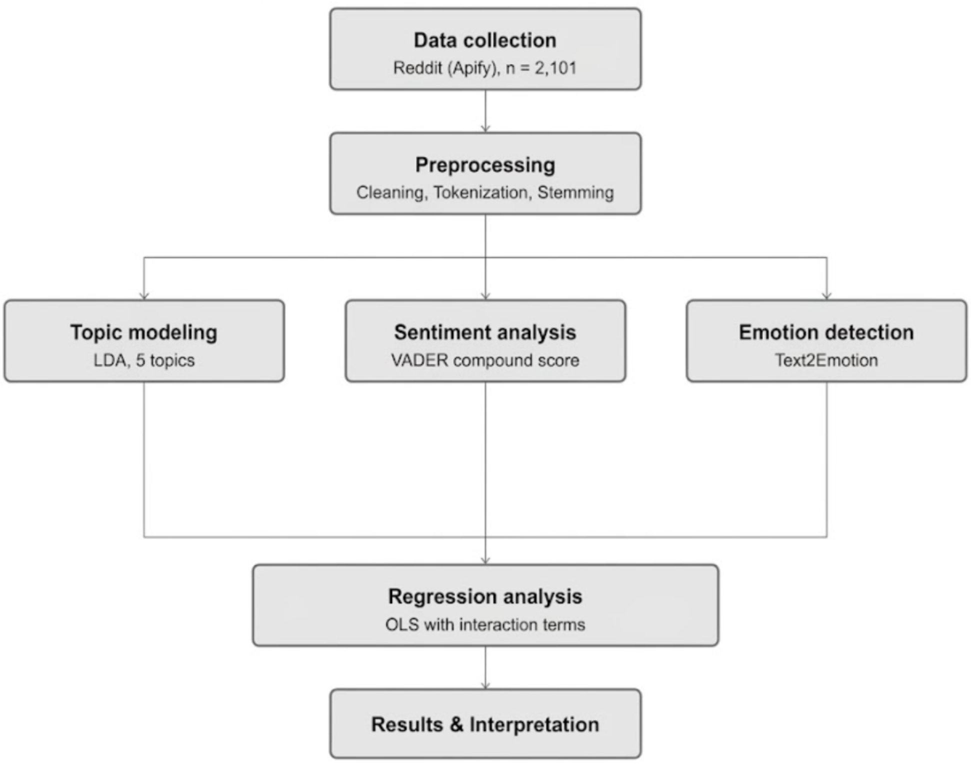
The integration of these findings reveals that emotions do not operate in a vacuum. Instead, their effects are contextually bound by individual- and situational-level factors. Ultimately, the effect of any emotion depends on its compatibility with the consumer's immediate environment and internal state (Aeron & Rahman, 2023).

3. Method

3.1 Research Design

This study adopts a quantitative, exploratory research design based on social media data analysis. The approach aims to identify patterns in how consumers discuss and engage with product trends, as well as how this links to online engagement. **Figure 2** provides an overview of the methodological process used in this study.

Figure 2: Overview of the Methodological Framework



In addition to the quantitative analysis, complementary desktop research has been conducted, including the review of articles, influencer content, and other online materials, to provide a broader understanding of the phenomenon.

The methodological approach is grounded in research arguing that web data represents a "goldmine" for marketing insights (Boegershausen et al., 2022). Building on this perspective, previous studies have increasingly combined social media data with quantitative text analysis techniques to analyze large volumes of user-generated content. To examine patterns within such online discussions, researchers have applied methods such as topic modeling, sentiment analysis, and emotion detection to identify underlying themes, emotional patterns, and behavioral dynamics. For example, KS (2024) demonstrates how social media data can be systematically analyzed to extract themes and emotional trends, while Tuan et al. (2024) show how these methods can be used to identify patterns and track changes in online communities over time. Similarly, Huang et al. (2025) illustrate how unstructured social media data can be transformed into structured and interpretable insights through supervised topic modeling. In addition, Aslam et al. (2022) demonstrate how sentiment analysis and emotion detection through Text2Emotion can be applied to large datasets to capture emotional responses in online communication. Overall, these studies suggest that integrating social media data with topic modeling, sentiment analysis, and emotion detection provides a reliable methodological approach for analyzing online behavior.

The relevance of this approach is further strengthened by research showing that social media activity is not isolated from real-world outcomes. Rather than existing separately from offline behavior, online discussions and interactions have been shown to reflect and influence real-world actions. For example, Korolov et al. (2016) demonstrate that social media activity can predict charitable donations, while Smith et al. (2023) show that online interactions are associated with participation in offline collective actions such as protests. These findings highlight the broader relevance of social media data and strengthen its usefulness for understanding consumer behavior beyond the digital context.

3.2 Reddit as a Data Source

Consumer discussions related to Labubu were collected from the social media platform Reddit, which served as the data source for this study. Reddit consists of thousands of user-driven communities where individuals interact through posts and discussions centered around shared interests. Through Reddit's upvote and downvote system, discussions that receive greater levels of user attention and engagement become more visible on the platform, allowing prominent themes and opinions to emerge organically (Reddit, 2026). In this study, consumer engagement was operationalized through upvotes. Upvotes were selected as the measure of engagement because they directly influence the visibility of content on Reddit (Reddit, 2026), making them particularly relevant in the context of viral trends. Furthermore, unlike some alternative engagement metrics, upvotes reduce the risk of disproportionate influence from a single user or spam account, as each account can only upvote a post or comment once. Consequently, upvotes provide a standardized indicator of collective community endorsement and engagement.

The platform's large scale and discussion-oriented structure further strengthen its suitability for this study. With millions of daily users across more than 100,000 active communities (Reddit, 2026), Reddit provides access to extensive volumes of user-generated content and ongoing consumer discussions. At the same time, the platform's relatively anonymous environment, where users frequently interact through pseudonyms, encourages more open and honest expression (Lee, 2018; Luarn et al., 2014). These characteristics make Reddit particularly valuable for capturing how consumers discuss and engage with trend-driven products such as Labubu.

3.3 Data Collection and Manual Preprocessing

The analysis is based on a dataset of 2,101 Reddit entries related to the Labubu phenomenon. The sample size was determined with reference to previous social media comment studies, where datasets commonly consisted of several thousand user comments (e.g., Naab et al., 2025, who analyzed 5,379 comments across discussion threads). In the present study, approximately 2,000 Reddit entries were considered sufficient due to Reddit's discussion-oriented structure (Reddit, 2026), which typically generates more reflective contributions compared to other social media platforms. As a result, each entry was expected to provide richer qualitative insights, meaning that analytical depth could be achieved with a comparatively smaller dataset while still ensuring thematic breadth and variation. After the data cleaning process, the final dataset consisted of 2,056 comments, 28 posts, and 17 missing values. As both comments and posts represent user-generated contributions to discussions on Reddit, they were treated equally and collectively referred to as Reddit entries.

To compile the dataset, relevant Reddit posts were first identified through Google's Advanced Search function. The keyword "Labubu" was used while restricting results to the domain reddit.com to capture a broad range of discussions related to the phenomenon on the platform. Posts were excluded if they were not directly related to the phenomenon being studied. For instance, posts that used Labubu primarily as a buzzword to attract attention, rather than discussing the phenomenon itself, were removed. However, no exclusions were made based on the sentiment or stance expressed toward Labubu. As the aim was to capture the phenomenon comprehensively, both positive and negative discussions were retained to reflect the diversity of opinions and experiences surrounding it. In addition, Google's filtering tools were used to limit results based on publication dates.

The selected period for data collection was determined in order to capture the development of the trend from its initial rise in popularity to the point where interest had largely declined. To identify this period, Google Trends was used as a supporting tool. More specifically, the "Labubu" topic was analyzed rather than a simple search term, since topics aggregate related searches across spelling variations, translations, and connected phrases (Google, n.d.). This provided a broader and more accurate representation of overall interest in the phenomenon over time, compared to a single search term that only captures exact phrasing entered by users.

The search interest for the selected topic was plotted as a line chart with interest on the y-axis and time on the x-axis. Based on this visualization, the time frame between 1 November 2024 and 28 February 2026 was identified. Within this period, Reddit posts were manually selected until the dataset reached approximately, but not less than, 2,000 entries (comments and posts). Since a maximum of 100 comments could be scraped per post, this approach helped reduce the influence of a small number of highly viral posts (with high amounts of comments) on the dataset.

Once the relevant Reddit posts had been identified, they were scraped to extract both the posts themselves and their corresponding comment discussions. The data was extracted using the web scraping platform Apify. More specifically, the "Reddit Scraper Lite" Actor was used by inputting the URLs of the selected posts and setting a maximum limit of 100 comments per post. The scraping process generated a dataset containing both textual content and engagement-related variables. These included the body text of posts and comments, publication timestamps (createdAt), upvotes, and metadata identifying whether the entry was a post or comment.

The extracted dataset was downloaded from Apify as an Excel file (.xlsx) containing 2,102 rows, where row 1 represented column titles. Following the extraction process, the dataset underwent an initial manual screening to prepare the data for analysis. Since the natural language processing (NLP) tools used for sentiment analysis, emotion detection, and topic modeling in this thesis are trained on English-language corpora, comments written in other languages were translated into English using DeepL.

Following the manual preprocessing stage, the dataset was converted from Excel (.xlsx) to CSV (.csv) format to prepare it for analysis.

3.4 Experimental Setup

The experiments were conducted in the Google Colab environment (Bisong, 2019), where Python 3 provided a flexible platform for data processing, natural language processing (NLP), and machine learning tasks. To support these different stages of the analysis, a range of Python libraries were used throughout the preprocessing, analysis, and visualization pipeline. **Table 2** provides an overview of the libraries applied in the study and their respective functions.

The preprocessing stage primarily relied on libraries designed for data handling and text preparation. Pandas (PyPI, 2026d) and NumPy (PyPI, 2026c) were used for data manipulation and numerical computations, while the Natural Language Toolkit (NLTK) (PyPI, 2026b) supported text preprocessing tasks such as tokenization, stopword removal, lemmatization, and stemming through the Porter Stemmer. In addition, regular expressions (re) (Python, 2026) were applied for text cleaning and pattern matching, whereas Beautiful Soup (bs4) (PyPI, 2025a) was used to parse and handle text data where necessary.

Once the textual data had been cleaned and prepared, the next step involved transforming the text into analyzable formats and extracting underlying patterns from the dataset. For this purpose, Scikit-learn's TF-IDF Vectorizer (Scikit learn, n.d.) was used to convert textual data into numerical representations suitable for analysis. Sentiment analysis was then conducted using NLTK's SentimentIntensityAnalyzer (NLTK, n.d.), while the Text2Emotion library (PyPI, 2020) was applied to identify emotional tones expressed within the discussions.

Topic modeling was then performed using Gensim (PyPI, 2025b), including corpus and model generation, while pyLDAvis (PyPI, 2023) was used to visualize and interpret the resulting topic models. Data visualization was further supported by Matplotlib (PyPI, 2026a) and Seaborn (PyPI, 2024), which were used to generate plots and graphical representations of the data.

Regression analysis was additionally conducted using the Statsmodels (PyPI, 2025c) library. An Ordinary Least Squares (OLS) model (Cumby & Huizinga, 1990) was employed to examine relationships between topics, sentiment, emotions, and Reddit post engagement. Interaction effects between topic categories and sentiment/emotion variables were also included in the model.

An overview of the Python libraries used throughout the analysis is presented in **Table 2**.

Table 2. *Python libraries used for the preprocessing and analysis of the dataset*

Library	Usage
Pandas	Data manipulation and analysis
NumPy	Numerical computations
NLTK (Natural Language Toolkit)	Text preprocessing, including tokenization, stopword removal, lemmatization, and stemming
re (Regular Expressions)	Text cleaning and pattern matching
BeautifulSoup (bs4)	Parsing and processing text/HTML data
Scikit-learn (TF-IDF Vectorizer)	Feature extraction, text vectorization, and preparation for statistical analysis
SentimentIntensityAnalyzer (NLTK)	Sentiment analysis
Text2Emotion	Emotion detection in text
Gensim	Topic modeling and corpus/model creation
pyLDAvis	Visualization and interpretation of topic models
Matplotlib and Seaborn	Data visualization
Statsmodels	Regression analysis and statistical modeling

3.5 Data Preprocessing

The text preprocessing steps employed in this study were designed to ensure that the data were thoroughly cleaned and standardized for the effective application of NLP techniques such as topic modeling and sentiment analysis. Initially, missing values in all columns were replaced with 0 so as not to reduce sample size or lose information by removing rows with missing data, consistent with Little and Rubin (2019).

The preprocessing procedure consisted of several sequential steps. First, the text was tokenized, meaning it was broken down into individual words or tokens, which form the basis for extracting meaningful patterns and features (Vijayarani & Janani, 2016). Following this, the text was cleaned by removing non-alphabetic characters and converting all text to lowercase. This step ensured consistency across the dataset and eliminated noise such as punctuation, URLs, user mentions, and other irrelevant symbols, allowing the analysis to focus on the substantive content of the posts. In addition, stopwords, meaning commonly used words with limited semantic value, were removed to reduce noise in the dataset and prevent less informative terms from disproportionately influencing the analysis (Manning et al., 2008).

Finally, stemming was applied to further standardize the text by reducing words to a common stem. This process allowed different variations of a word to be treated as a single term, thereby improving information retrieval performance by reducing vocabulary size and enhancing the matching of related terms (Porter, 2006). Once these steps were completed, the processed tokens were transformed back into text format, resulting in cleaned versions of the original comments and posts. Collectively, these preprocessing procedures ensured that the textual data were appropriately prepared for subsequent NLP applications, enabling more accurate and reliable topic modeling, sentiment, and emotion analysis.

3.6 Sentiment Analysis & Emotion Detection

The sentiment analysis was conducted using the Valence Aware Dictionary and sEntiment Reasoner (VADER), implemented through the Natural Language Toolkit (NLTK). VADER is a lexicon- and rule-based sentiment analysis tool specifically designed for social media text (Hutto & Gilbert, 2014), making it well-suited for analyzing user-generated content such as Reddit comments. Sentiment polarity scores were calculated for each post, resulting in a compound score ranging from −1 (most negative) to +1 (most positive), providing an overall measure of sentiment. Based on the compound score, each entry was classified as positive (compound > 0.05), negative (compound < −0.05), or neutral (between −0.05 and 0.05), allowing for a structured interpretation of sentiment distribution within the dataset. For example, the comment "I think these are SO adorable, I love them" is positive, "Don't understand the appeal of these ugly [...] characters" is negative, and "They've started to trend in the last couple months" is neutral.

While the polarity analysis captured the overall positive or negative orientation of the discussions, a more detailed understanding of emotional expression required a more fine-grained analysis of specific emotions. Therefore, emotional tone was further examined using the Text2Emotion library, which extracts the emotion categories: happy, angry, surprise, sad, and fear. For each row in the dataset, the model generated a score between 0 and 1 for each emotion category, representing the relative intensity or presence of that emotion within the text. For example, the statement “[...] they make me smile” is primarily happy, “Only dumb people like to buy those” is angry, “[...] I’m legitimately dumbfounded” is surprised, “[...] I gave up” is sad, and “It is addictive as gambling.” is fearful. The sentiment and emotion classifications were manually verified through a small sample of selected entries to assess whether the assigned classifications were consistent with the researchers’ interpretations of the text.

3.7 Topic Modeling

Latent Dirichlet Allocation (LDA) was employed to uncover latent thematic structures within the text data, leveraging its role as a generative probabilistic model widely used for topic discovery in natural language processing (Jelodar et al., 2018). The process began with preparing the preprocessed text data by converting the cleaned text strings into tokenized lists, enabling their use in the modeling procedure.

Next, a dictionary was constructed using the Gensim library, where each unique token in the dataset was assigned a corresponding identifier. This dictionary was then used to construct the corpus, representing each document as a bag-of-words vector based on the frequency of tokens within the text. Through this transformation, the textual data was converted into a numerical format suitable for topic modeling (Srinivasa-Desikan, 2018).

The LDA model was then defined and trained using the Gensim implementation. The number of topics was set to five following a manual evaluation process aimed at balancing specificity and distinctiveness, as too few topics produced overly broad themes while too many created narrow and overlapping ones within our dataset. To determine the most suitable configuration, the model was repeatedly built and visualized using different topic numbers, after which the associated keywords and separation between topics were evaluated to assess coherence and distinctiveness. When too many topics were specified, the visualization indicated substantial overlap between topics, with several topics sharing similar keywords and thematic content. Conversely, when too few topics were selected, conceptually distinct themes were grouped together within the same topic, reducing thematic specificity and potentially obscuring important nuances in the subsequent analysis. The model was also configured with a fixed random state to ensure reproducibility. During training, LDA assumes that each document consists of a mixture of topics, while each topic is represented through a distribution of words (Jelodar et al., 2018), enabling the model to identify the dataset's underlying thematic structure.

The resulting topics were visualized using the pyLDAvis library, which provides an interactive representation of topic distributions and their relationships (Sievert & Shirley, 2014). This visualization facilitated the interpretation of the topics by illustrating their relative prevalence and the most relevant terms associated with each topic. Through this process, meaningful themes were identified, providing insight into the dominant discussions within the dataset.

Finally, the labeling of topics was carried out through an interpretative process. Specifically, frequently occurring and highly weighted words within each topic were analyzed to identify underlying semantic patterns. Based on these patterns, descriptive labels were assigned to each topic. Thus, topic labels were derived from recurring word combinations and their contextual meaning within the dataset. This approach ensured that the assigned labels offer a meaningful and reliable representation of the thematic content of each topic, enhancing the overall interpretability of the results (Jelodar et al., 2018).

3.8 Linear Regression

Prior to the regression analysis, a correlation analysis was conducted to assess potential multicollinearity among the independent variables, since high correlations between explanatory variables can distort regression estimates and reduce the reliability of model coefficients (Kim, 2019). To evaluate this, Pearson correlation coefficients were calculated for all variables included in the model and visualized through a heatmap. The analysis included the dependent variable, log-transformed upvotes (log_upvotes), sentiment and emotion variables (compound, happy, angry, surprise, sad, and fear), as well as topic dummy variables. To enable the inclusion of categorical topics in the statistical analysis, the topic variables were transformed into binary dummy variables (0/1).

Additionally, the upvote variable was log-transformed using the natural logarithm function (log1p) to reduce skewness in the distribution of Reddit engagement. Since social media engagement (in this case Reddit upvotes) can be highly unevenly distributed, where a small number of viral posts receive disproportionately high attention (Sangiorgio et al., 2025), the log transformation compressed extreme values while preserving the relative ranking of entries. This improved the suitability of the data for correlation and regression analyses.

After confirming that multicollinearity was not severe enough to compromise the analysis, specifically that all Pearson correlation coefficients were below 0.8 (Shrestha, 2020), a multiple linear regression model was estimated using Ordinary Least Squares (OLS). The purpose of the regression was to examine how topics, sentiment, and emotions were associated with Reddit post engagement, measured through log-transformed upvotes.

The regression model was specified as:

$$\log(\text{upvotes}) \sim C(\text{topic}) \times (\text{compound} + \text{happy} + \text{angry} + \text{surprise} + \text{sad} + \text{fear})$$

In the regression model, C(topic) was treated as a categorical variable with Topic 1 serving as the reference category. The choice of reference category is important because it determines how comparisons between categories are interpreted (Johfre & Freese, 2021). Previous research further suggests that the reference category should align with the purpose of the study while avoiding very small categories that may increase multicollinearity (Wissmann et al., 2011). Based on these considerations, Topic 1 was selected as the reference category due to its theoretical relevance, interpretability, and relatively large size within the dataset compared to other topics. More specifically, Topic 1 reflected a market-oriented understanding of the product, centered on scarcity, collectibility, and resale, making it possible to interpret how the remaining topics differ from this framing and how broader social, identity-based, and community-related meanings relate to engagement, as the remaining topics are more strongly centered around these dimensions.

Given these thematic differences between topics, interaction terms were included to examine whether the effects of sentiment and emotions on engagement varied depending on the topic (discussion context).

The interaction operator (x) therefore incorporated both main effects and interaction effects between topics and each sentiment/emotion variable. This made it possible to assess not only whether emotions and sentiment were associated with engagement overall, but also whether their relationships with engagement differed across the various thematic framings identified in the topic modeling analysis. The inclusion of interaction terms therefore provided a more nuanced understanding of how the relationship between emotional expressions and engagement may vary across different discussion topics. To estimate these relationships, the regression model was conducted using the statsmodels library in Python. The Ordinary Least Squares (OLS) approach was selected because it allows for the examination of linear relationships between independent and dependent variables while simultaneously controlling for multiple predictors.

The explanatory power of the regression model was evaluated using both R^2 and Adjusted R^2. While R^2 measures the proportion of variance in log-transformed upvotes explained by the independent variables, Adjusted R^2 accounts for the number of predictors and interaction terms included in the model, making it more suitable for multiple regression analysis. A high explanatory power was not expected, as Reddit engagement is influenced by many additional factors beyond discussion topics, sentiment, and emotions, such as posting time, subreddit size, and algorithmic visibility. Therefore, the purpose of the model was not to fully predict engagement, but rather to examine whether topics, sentiment and emotional expressions had meaningful relationships with upvote levels. In this thesis, a cut-off of $p \leq 0.05$ was used to determine statistical significance, as Andrade (2019) explains that 0.05 is generally applied as the threshold for statistical significance.

3.9 Methodological considerations

While the methodological approach adopted in this study enables a structured and data-driven analysis of user-generated content, certain limitations should be acknowledged. The dataset is based on Reddit data, which provides rich and relevant insights into online discussions but represents a specific subset of the population, characterized by a relatively younger and more male-dominated user base, with a strong presence in the United States (Duarte, 2025). In addition, the data collection process relied on the defined keyword “Labubu” together with Google’s search functionality, meaning that while the dataset captures a substantial and relevant sample of discussions, it may not be fully exhaustive. The manual post-selection process further introduces a potential source of subjectivity, as decisions regarding inclusion were partly guided by researcher judgment. To reduce this bias, care was taken to include a diverse range of perspectives and discussions reflecting different aspects of the Labubu phenomenon. However, the comments themselves were automatically collected through

Apify, with a maximum of 100 comments extracted per post, thereby reducing the risk of researcher bias in the comment selection process. To further improve representativeness, care was also taken to include posts across the full investigated timeframe.

Additionally, while NLP techniques such as sentiment analysis and topic modeling are well-established methods for analyzing large-scale text data (KS, 2024; Tuan et al., 2024; Huang et al., 2025; Aslam et al., 2022), they have certain limitations, including challenges in capturing nuanced language (e.g., sarcasm) (Joshi et al., 2017) and the need for manual interpretative topic labeling. Despite these considerations, the overall methodological approach is systematic, transparent, and grounded in established analytical techniques, supporting the credibility and robustness of the findings.

4. Results

The results are organized into (1) preliminary descriptive and data analyses, followed by (2) the main regression analyses examining the relationship between Reddit engagement, topics, sentiment and emotions.

4.1 Preliminary Analyses

4.1.1 Topic Identification and Classification

To identify the main discussion themes within the Reddit dataset, topic modeling was conducted on the collected entries. The analysis generated five distinct topics based on recurring word patterns and semantic similarities between entries. Following the topic-modeling procedure, each topic was manually interpreted and classified by analyzing the most representative keywords for each topic.

Topic 1: The first identified topic reflected scarcity-driven collectible market behavior. Entries within this category focused on buying, collecting, reselling, and obtaining rare products, often connected to blind-box or gambling-like purchasing mechanisms. Representative keywords included *"buy," "collect," "want," "find," "set," "blind," "gamble," "sell,"* and *"resell."*

Topic 2: The second topic represented socially driven attachment, where discussions centered around trends, popularity, and emotional attachment to the product. Consumers frequently referred to collective interest, hype, and social influence. Keywords such as *"like," "love," "people," "trend", "interest", "bought", "craze"* and *"market"* characterized this topic.

Topic 3: The third topic reflected online community participation. This category included discussions occurring within digital platforms where users exchanged information, opinions, and experiences related to the product. Common keywords included *"app," "subreddit," "post," "comment," "question," "talk", "thank," "get", "social", "friend"* and *"heard."*

Topic 4: The fourth topic captured fan-driven obsession, characterized by celebrity influence, emotional attachment, and fan-related consumption behavior. Discussions frequently referenced celebrities and fandom culture, particularly connected to *Blackpink* and *Lisa*. Representative keywords included *"see", "saw", "obsess", "lisa", "blackpink", "go", "first", "consum[e]."*

Topic 5: Finally, the fifth topic reflected identity expression, where consumers used the product as a form of self-presentation and aesthetic expression. Posts focused on style, appearance, and personal taste, while also containing polarized opinions regarding attractiveness and design. Keywords associated with this topic included *"person", "bag", "look", "like", "charm", "wear", "cute,"* and *"ugly."*

The identified topics were subsequently used in further analyses to examine how different discussion themes related to Reddit engagement both independently and in combination with sentiment and emotions.

4.1.2 Descriptives

The results showed that Topic 1 accounted for the largest share of tokens (24.3%), followed by Topic 2 (22.8%), Topic 3 (19.7%), Topic 4 (18.1%), and Topic 5 (15.1%). The sentiment analysis further revealed that the majority of observations expressed a positive sentiment. Out of the 2,101 entries, 1,092 were classified as positive, compared to 683 neutral and 326 negative comments. The emotion analysis showed that happiness ($M = 0.194$) and fear ($M = 0.188$) were the most dominant emotions, followed by sadness ($M = 0.156$) and surprise ($M = 0.105$), while anger had the lowest average score ($M = 0.051$).

4.2 Correlation Analysis

A Pearson correlation analysis was conducted between Reddit engagement, topics, sentiment, and emotions. Overall, most correlations were relatively weak, indicating low risk for multicollinearity. The strongest positive correlation was identified between compound sentiment and happiness ($r = 0.42$), and the strongest negative correlation was observed between Topic 1 and Topic 4 ($r = –0.34$).

4.3 Linear Regression Analysis

The regression model was statistically significant overall, $F = 3.189$, $p < .001$. However, the explanatory power of the model remained relatively modest ($R^2 = .050$; Adjusted $R^2 = .034$).

4.3.1 Main Effects of Topics

The regression results showed that certain topics were associated with significantly different engagement levels compared to the reference category, Topic 1, which served as the baseline for comparison. Topic 2 displayed a non-significant negative relationship with engagement ($\beta = –0.123$, $p = .487$). In contrast, Topic 3 demonstrated a significant positive relationship with engagement ($\beta = 0.434$, $p = .012$), while Topic 4 showed a positive but non-significant association ($\beta = 0.285$, $p = .080$). Topic 5 exhibited the strongest effect, showing a significant positive relationship with engagement ($\beta = 0.573$, $p = .001$).

4.3.2 Main Effects of Sentiment and Emotions

The emotional variables produced mixed results in relation to engagement. Compound sentiment was not significantly associated with engagement ($\beta = 0.052$, $p = .743$). However, several specific emotional categories demonstrated significant positive relationships with engagement. Surprise was positively associated with engagement ($\beta = 0.618$, $p = .013$), while sadness was also positively and significantly associated with engagement ($\beta = 0.646$, $p = .001$). Fear showed the strongest positive association with engagement in the model ($\beta = 0.822$, $p < .001$). In contrast, happiness ($\beta = 0.284$, $p = .223$) and anger ($\beta = 0.375$, $p = .349$) were not significantly associated with engagement levels.

4.3.3 Interaction Effects Between Topics and Emotions

To further investigate whether the relationships between emotions and engagement differed depending on the discussion topic, interaction terms between topics and sentiment/emotional variables were included in the regression model. Several statistically significant interaction effects emerged. The interaction between Topic 5 and compound sentiment showed a significant negative effect ($\beta = -0.791$, $p = .003$). Similarly, significant negative interactions were identified between fear and multiple topics, including Topic 2 × Fear ($\beta = -0.888$, $p = .005$), Topic 3 × Fear ($\beta = -0.906$, $p = .008$), and Topic 5 × Fear ($\beta = -0.753$, $p = .028$). No additional statistically significant interaction effects were observed.

4.3.4 Summary of Main Findings

The results reveal several important patterns regarding Reddit engagement in discussions about Labubu. Engagement varied significantly across topics, with Topic 3 and Topic 5 showing a positive association with higher engagement levels. Emotional expressions also played a key role, specifically fear, surprise, and sadness, which demonstrated positive relationships with engagement. Furthermore, the interaction analyses showed that the impact of emotions and sentiment differed depending on the discussion topic, suggesting that engagement is shaped not only by sentiment or emotion itself but also by the topic of the conversation. Although the regression model was statistically significant overall, the relatively low Adjusted R^2 value indicates that engagement is also influenced by additional factors. Overall, the findings suggest that topic, sentiment, and emotional tone all contribute meaningfully to engagement in online discussions about Labubu.

5. Discussion & Implications

5.1. Addressing the Research Questions

At the outset of this thesis, a set of research questions was proposed to examine consumer discussions surrounding the Labubu phenomenon, and how socially embedded dynamics are reflected in consumer discussions and engagement. The findings presented in the following sections provide the basis for addressing each of these research questions.

RQ1: To what extent are specific discussion topics associated with higher levels of consumer engagement within the Labubu trend?

The findings reveal that certain discussion topics were associated with substantially higher levels of engagement than others. In particular, discussions centered around online community participation demonstrated a clear positive relationship with engagement, indicating that posts emphasizing shared discussions, collective participation, and community involvement tended to generate comparatively high levels of interaction within the dataset. Similarly, discussions related to identity expression also demonstrated a strong positive association with engagement, suggesting that entries in which consumers connected Labubu to self-expression, personal identity, and/or style generated particularly high levels of consumer engagement.

In contrast, discussions characterized by socially driven attachment and fan-driven engagement did not demonstrate a statistically significant relationship with engagement levels. No relationship between scarcity-driven collectible market behavior and engagement was investigated since it was used as the reference topic for the regression.

RQ2: How are sentiment patterns related to consumer engagement with the Labubu phenomenon?

The findings indicate that overall sentiment polarity did not demonstrate a statistically significant relationship with engagement levels. More specifically, whether discussions surrounding Labubu were characterized by more positive or negative overall sentiment did not appear to significantly relate to the level of consumer interaction measured through Reddit engagement.

RQ3: How are emotional expressions related to consumer engagement with the Labubu phenomenon?

The findings reveal that several specific emotional expressions demonstrated meaningful relationships with engagement levels. In particular, discussions characterized by surprise, sadness, and fear were associated with substantially higher levels of consumer engagement. Among these emotions, fear demonstrated the strongest relationship with engagement, suggesting that discussions reflecting uncertainty and apprehension tended to generate particularly high levels of interaction. Similarly, entries characterized by sadness and surprise also appeared to attract comparatively strong engagement, indicating that emotional discomfort and unexpected discussions surrounding Labubu were more likely to stimulate consumer engagement. In contrast, happiness and anger did not demonstrate significant relationships with engagement levels.

RQ4: How do discussion topics moderate the relationship between sentiment and engagement?

The findings reveal that discussions related to identity expression in interaction with sentiment demonstrated a significant relationship with engagement, indicating that the relationship between sentiment and engagement was moderated by the discussion context. More specifically, increasingly positive sentiment within identity-related discussions was associated with comparatively lower engagement levels. Instead, discussions characterized by neutral or negative sentiment appeared to generate comparatively stronger interaction. These findings suggest that the relationship between sentiment and engagement was not uniform across discussion topics. Rather, the association between sentiment and engagement appeared to vary across thematic contexts in which it was expressed.

The findings reveal that the relationship between emotional expressions and engagement varied depending on the underlying discussion topic. In particular, several significant interaction effects emerged between fear and specific discussion topics, indicating that the link between fear and engagement was not consistent across all topics of discussions surrounding Labubu. More specifically, discussions characterized by socially driven attachment, online community participation, and identity expression all demonstrated significant negative interactions with fear. These findings suggest that although fear generally demonstrated a strong positive relationship with engagement overall, this positive association weakened substantially within these specific discussion contexts.

5.2 General Discussion

This thesis set out to examine which factors are associated with consumer engagement in rapidly evolving trends. Our findings suggest that trend diffusion is associated with socially embedded dynamics such as identity expression, online community participation and emotional drivers. Rather than requiring a clearly articulated understanding of Labubu, consumers appear to have interpreted the phenomenon through digitally mediated social cues, consistent with Deval et al.'s (2013) discussion of inferential strategies and Consumer Culture Theory's emphasis on how consumers construct meaning through socially embedded consumption practices (Arnould & Thompson, 2005).

One of the most significant findings concerns the relationship between emotions and engagement. Although overall sentiment polarity did not significantly predict engagement, specific emotions such as fear, sadness, and surprise showed strong positive relationships with engagement levels. Among these emotions, fear was associated with the highest levels of engagement, suggesting that uncertainty-related emotional expressions were particularly prominent in highly engaged discussions surrounding the phenomenon. This finding aligns with previous research on fear of missing out (FOMO), which argues that FOMO promotes action-oriented consumer behaviors such as impulsive purchasing and a heightened sense of urgency (Aydın, 2019; Tang et al., 2025). Subsequently, such behavior may coincide with higher levels of engagement. The findings further support Griskevicius et al. (2009), who argue that fear increases individuals' reliance on social proof under conditions of uncertainty, as well as Chen and Pham (2018), who suggest that fear motivates affiliation-seeking behavior as a way to reduce uncertainty. Together, this indicates that fear may be associated with individuals engaging more actively with others during uncertain situations. However, the extent to which individuals respond to uncertainty may vary depending on individual characteristics. For example, Argan et al. (2022) show that a stronger need for uniqueness increases susceptibility to FOMO, which may indicate that the desire for uniqueness was particularly strong among individuals within our dataset.

However, the interaction analyses showed that the positive association between fear and engagement was weaker in discussions centered around community participation, identity expression, and social attachment. This suggests that uncertainty-based motivations became less important once consumers became socially embedded within communities and increasingly connected the product to identity and belonging. More specifically, online community participation, socially driven attachment, and identity expression all moderated the relationship between fear and engagement. This indicates that engagement shifted away from uncertainty-related exploration as participation appeared to be increasingly associated with community belonging, socially validated participation, and symbolic identification. These social and identity-related factors may have provided emotional stability and reduced feelings of uncertainty, which is consistent with Katz et al.'s (2020) discussion of self-categorization and group alignment.

A similar pattern can also help explain the positive relationship between sadness and engagement. Sadness demonstrated a significant positive relationship with engagement, which may be linked to previous research associating sadness with compensatory behavior (Raghunathan & Pham, 1999). In this context, consumers may have experienced sadness when they were unable to access or participate in the trend, particularly because highly visible consumption can function as a signal of group affiliation, while adoption serves as a means of achieving social integration (Bearden & Etzel, 1982; Fisher & Price, 1992). Furthermore, because sadness has been shown to motivate individuals to seek support (Aeron & Rahman, 2023), discussions characterized by sadness may be associated with higher engagement among users experiencing similar emotions and seeking social support from others.

Surprise similarly showed a strong positive relationship with engagement, indicating that unexpected and novel experiences played an important role in stimulating engagement. Prior research suggests that surprise increases attention and motivates consumers to process the experience with others (Derbaix & Vanhamme, 2003), which could lead them to engage with posts expressing surprise. In the context of Labubu, the blind-box purchasing format likely intensified these dynamics by creating uncertainty and unpredictability surrounding product outcomes. Surprise may therefore have emerged through unboxing experiences and rare product discoveries, which coincided with higher levels of engagement.

Moving on to identity expression, the findings showed a strong positive relationship between this topic and engagement. Discussions related to identity expression, such as style, aesthetic expression, and self-presentation, were associated with particularly high levels of engagement. This suggests that consumers used Labubu as a symbolic resource for identity construction, which supports Wiklund and Gollwitzer's (1981) theory of self-completion as well as Sirgy's (1982) theory of self-congruity.

This relationship between identity expression and engagement became even clearer in the interaction analyses, where identity-related discussions were found to moderate the relationship between sentiment and engagement. More specifically, more neutral or negative discussions about identity expression through Labubu were associated with comparatively higher levels of engagement, possibly reflecting greater levels of opinion sharing and collective evaluation of the product. Since identity-related consumption is closely connected to symbolic self-expression and social signaling (Wiklund & Gollwitzer, 1981; Sirgy, 1982), discussions containing mixed, subjective, or even conflicting opinions may have appeared more engaging and relatable than uniformly positive content. This may be particularly relevant in the case of Labubu's distinctive "cute-ugly" aesthetic, where engagement seems to emerge through ongoing social interpretation and discussion rather than through clear consensus. Such findings also align with research suggesting that moderately atypical products are often perceived as more attractive and interesting by potential buyers (Formilan et al., 2021).

Beyond identity expression, engagement was also strongly associated with social and community-oriented dynamics The strong relationship between online community participation and engagement suggests that consumers engaged more with content that fostered a sense of community and shared participation within brand communities (Marchowska-Raza & Rowley, 2024; Katz et al., 2020). Because interactions within online brand communities often extend across weak ties, such content may also spread more easily between otherwise disconnected social groups, further amplifying engagement (Granovetter, 1973). This reasoning may therefore help explain why community-related comments and posts were associated with particularly high levels of engagement.

On the contrary, the results showed that socially driven attachment did not have a statistically significant relationship with engagement. Prior research within this area primarily emphasizes the relationship between social influence and consumer choices, adoption behavior, and purchase intentions, highlighting factors such as bandwagon effects, peer influence, and eWOM (Leibenstein, 1950; Cialdini & Goldstein, 2004; Nadroo et al., 2024; Li et al., 2025). Combined with the findings of the present study, this may suggest that socially driven attachment is related to how consumers evaluate and adopt products, while not showing a significant relationship with engagement in the present context. From a theoretical perspective, the result may indicate that social influence is more closely associated with consumer evaluation and adoption processes than with engagement, at least within the context of this study.

Additionally, our results showed that fan-driven obsession did not have a statistically significant relationship with engagement. However, prior research primarily links celebrity worship and fandom-related behavior to purchase intention, impulsive buying behavior, and brand attractiveness rather than engagement specifically (Aw et al., 2020; Chen et al., 2022; Zafar et al., 2021). Previous studies further show that repeated exposure to influencer content strengthens parasocial relationships and psychological connections with influencers over time, while emotional attachment to celebrities may also transfer to endorsed brands (Xie & Feng, 2022; Suprawan et al., 2025; Aw et al., 2020). Thus, this may indicate that fan-driven obsession is associated with emotional reactions rather than higher levels of engagement. Although celebrity worship and parasocial relationships can strengthen emotional attachment and behavioral intentions, such relationships may depend on continuous exposure and therefore may not necessarily be associated with deeper engagement.

This pattern also became visible in some of the emotional findings, where certain emotions were not significantly associated with engagement. More specifically, our results showed that happiness and anger did not have a statistically significant relationship with engagement. Happiness, which is considered a high-certainty positive emotion associated with positive affect and expanded thought-action tendencies (Aeron & Rahman, 2023). Anger, on the other hand, is a negative emotion associated with reactions such as frustration, confrontation, and complaints (Antonetti, 2016; Bougie et al., 2003). Previous research further connects anger to switching behavior, negative evaluations, and simplified decision-making processes (Garg et al., 2005; Chen & Pham, 2018). However, despite these behavioral associations, neither happiness nor anger were significantly associated with engagement in our findings. This may indicate that the relationship between these emotions and engagement depends heavily on contextual and situational factors, making the observed associations less consistent across different contexts. Consequently, happiness and/or anger alone may not necessarily be associated with stronger consumer engagement.

5.2.1 Theoretical Contributions

Foremost, our thesis extends existing research by demonstrating how contemporary social media platforms accelerate the diffusion of consumer trends by making products constantly visible and socially reinforced across online networks. The findings further suggest that these platforms no longer merely function as communication channels, but increasingly operate as central environments where consumers actively shape and reinforce trends through emotional engagement, participation in online communities, and identity expression. This thesis expands the understanding of consumer behavior in digital environments, while also contributing to research on emotions in consumer behavior, community and social consumption, and the symbolic and status-related meaning of products, which are discussed in the following sections.

Diving deeper, our findings contribute to research on emotions in consumer behavior by showing how emotional responses are associated with engagement in digital environments. Previous research has shown that emotions influence evaluations and behavior (Sharma et al., 2023; Aeron & Rahman, 2023) and that specific emotions are more important than simply distinguishing between positive and negative sentiment (Lerner & Keltner, 2000). Extending this literature, we found that fear, sadness, and surprise were more strongly associated with engagement than overall sentiment polarity, with fear exhibiting the strongest relationship with engagement. Earlier studies have primarily linked fear to affiliation-seeking behavior, social proof, and FOMO-driven consumption (Chen & Pham, 2018; Griskevicius et al., 2009; Good & Hyman, 2020). But we extend this research by showing that similar patterns can also be observed within digital engagement contexts, where fear is associated not only with consumption-related motivations, but also with online interaction and participation surrounding the trend itself.

At the same time, the interaction effects revealed that the positive relationship between fear and engagement was weaker in discussions centered around online community participation, identity expression, and socially driven attachment. Existing theory suggests that consumers seek affiliation, belonging, and self-categorization in order to strengthen social connectedness (Osei-Frimpong et al., 2022; Katz et al., 2020). Our findings build on this perspective by indicating that, once consumers become socially embedded within online communities and increasingly connect the product to identity and belonging, uncertainty-related emotions such as fear become less strongly associated with engagement. Instead, engagement appears to shift from being motivated by uncertainty toward more socially stabilized and identity-based forms of participation. This suggests that digitally diffused trends may gradually evolve from uncertainty-driven engagement into more community-oriented and identity-driven consumer behavior.

While the positive relationship between fear and engagement was weaker in discussions characterized by online community participation, other emotions continued to demonstrate significant relationships with engagement within digital consumer environments. More specifically, the positive relationship between sadness and engagement extends prior research suggesting that sadness motivates compensatory behavior aimed at coping with feelings of loss and helplessness (Raghunathan & Pham, 1999). Whereas previous research has primarily focused on how sadness influences individual consumption decisions, our findings contribute by showing that sadness may also be associated with engagement within digital consumer communities. A similar pattern emerged for surprise. Although surprise appeared less frequently in the discussions, it was associated with disproportionately high levels of engagement when present. Previous studies suggest that surprise intensifies attention and motivates consumers to process unexpected experiences together with others (Derbaix & Vanhamme, 2003). Our findings extend this perspective by showing that, in digital consumer environments, surprise not only captures attention but also appears to coincide with observable forms of online engagement. Taken together, our study advances the understanding of emotion research by showing that emotions in digital consumer environments are associated not only with individual consumer responses, but also with online engagement surrounding consumer trends.

Several of these emotions appear to be associated with interaction and discussion among consumers, and our findings also highlight the relationship between online communities and engagement surrounding digital consumer trends. Consumers derive value not only from products themselves, but also from the social relationships and interactions surrounding them (Marchowska-Raza & Rowley, 2024; Katz et al., 2020). Extending this knowledge, our findings show that discussions centered around online community participation were associated with some of the highest levels of consumer interaction, suggesting a strong relationship between engagement in digitally embedded consumer trends and collective interaction and social participation. The findings further support previous research on emotional support, group belonging, and value creation within brand communities (Schau et al., 2009; Osei-Frimpong et al., 2022; Katz et al., 2020), but add by showing that digital communities are associated with consumer interest and engagement surrounding rapidly spreading consumer trends.

Further, this study contributes by adding to previous literature establishing that consumers use products symbolically to communicate identity, belonging, and status (Wiklund & Gollwitzer, 1981; Sirgy, 1986; Eastman et al., 1999). Our findings extend this research by showing that identity-related content was associated with some of the highest levels of engagement, suggesting that identity signaling is closely associated with engagement in highly visible and rapidly diffusing digital trends. The findings therefore contribute to a broader understanding of how contemporary consumers construct and communicate their identity through interaction in digital environments.

Finally, we add nuance to research emphasizing that positive emotions strengthen favorable consumer responses and evaluations (Forgas, 1995), as well as contributing to research suggesting that the effect of sentiment depends on the situation and the surrounding environment (Fredrickson, 1998; Griskevicius et al., 2010; Raghunathan & Pham, 1999). Our findings contribute to a more contextualized understanding of this relationship by specifically examining how identity-related discussions moderate the relationship between sentiment and engagement in digital consumer environments. The results suggest that engagement surrounding identity-expressive products is more strongly associated with emotionally mixed or polarized discussions than with uniformly positive evaluations. This indicates that disagreement and conflicting interpretations surrounding symbolic products are closely associated with engagement within rapidly diffusing digital consumer trends.

5.2.2 Managerial Implications

The findings emphasize the strategic importance of online communities in maintaining consumer engagement. Previous research has shown that consumers derive value not only from products themselves, but also from the emotional support, group belonging, social relationships, and interactions surrounding brand communities (Schau et al., 2009; Osei-Frimpong et al., 2022; Marchowska-Raza & Rowley, 2024; Katz et al., 2020). Consistent with this, community-related discussions were associated with particularly high levels of engagement within the dataset, highlighting an opportunity for companies to strengthen engagement by facilitating spaces where consumer communities can naturally form and interact, either through their own brand-owned digital platforms or through an active presence across social media channels. In connection to brand-owned digital platforms, companies should aim to strengthen what Wichmann et al. (2021) describe as the “community block” through social exchange, where consumers engage in ongoing interaction that creates a sense of belonging with other community members. Such communities may help sustain continuous visibility and consumer interest surrounding products beyond traditional one-directional marketing communication, suggesting that managers should view communities not simply as audiences, but as active contributors to sustaining trend momentum and reinforcing consumer interest over time.

Further, the findings suggest that engagement around symbolic and identity-expressive products is not necessarily associated with uniformly positive sentiment, but rather with emotionally mixed and polarized discussions, despite previous research emphasizing that positive emotions strengthen favorable consumer responses (Forgas, 1995). Since consumers use products symbolically to communicate identity, belonging, and status (Wiklund & Gollwitzer, 1981; Sirgy, 1986; Eastman et al., 1999), brands can benefit from recognizing that symbolically ambiguous products may be associated with stronger consumer engagement when consumers are able to attach their own meanings and identities to them. This highlights the importance of facilitating consumer participation and identity signaling in digital environments, such as brand platforms and social media channels, rather than attempting to maintain fully controlled or universally positive brand interpretations. One way of enabling this is through further developing how brands utilize brand-owned digital platforms, for instance by incorporating the “inspiration block” to foster creativity, exploration, and idea-sharing (Wichmann et al., 2021).

By combining the community and inspiration building blocks, identified by Wichmann et al. (2021), brands can create a brand-owned digital platform that facilitates both consumer crowdsourcing and crowdsending, where consumer crowdsourcing refers to consumers deriving value from platform participants, and crowdsending involves consumers contributing value back to these participants. This matters for managers since it fosters deep, ongoing connections between the brand and consumers. Over time, the platform can become integrated into consumers’ identities by strengthening emotional attachment and creating some of the most enduring brand relationships.

Lastly, research highlights that emotions influence consumer evaluations and behaviors (Sharma et al., 2023; Aeron & Rahman, 2023). Moreover, our findings indicate that consumer engagement in digital environments was most strongly linked to emotions such as fear, sadness, and surprise. Brands managing digitally diffused trends should therefore recognize that uncertainty, emotional discomfort, and unexpected content may be associated with higher levels of engagement. One possible approach is to utilize elements of mysterious consumption, where consumers engage with products or experiences without full knowledge of their exact nature (Ding & Han, 2024), thereby leveraging novelty and uncertainty. However, our findings show that as consumers become more socially connected and emotionally attached to the trend, managers should shift focus from uncertainty (fear) toward strengthening community, belonging, and identity expression, as the positive relationship between uncertainty and engagement was weaker in these contexts.

5.2.3 Limitations and Future Research

First, a limitation of this study is that it focuses on a single product case, namely the Labubu phenomenon, which may limit the generalizability of the findings. Although Labubu represents a relevant example of how digitally driven trends can spread through social media, some of the identified factors associated with engagement may be specific to this particular phenomenon. Prior research suggests that examining multiple cases can provide deeper insight into complex social phenomena and support broader theory development across different contexts (Eisenhardt, 1989; Flyvbjerg, 2006). By comparing both similar and different cases, researchers may also move beyond simplistic interpretations and develop a more nuanced understanding of underlying patterns and relationships (Eisenhardt, 1989). Future research could therefore extend this study by investigating additional trend-driven products shaped by similar digital dynamics, such as Stanley Cups (a waterbottle), Jellycats (a plush-toy) and Prime Energy (a sports drink) to name a few, which have likewise gained rapid popularity through social media visibility, influencer exposure, and online communities (Demopoulos, 2024; Jibril, 2025; Gull McElroy, 2023). When choosing another viral product and/or comparing multiple cases, future studies could develop a broader understanding of whether the identified factors associated with engagement reflect more general patterns across rapidly evolving digital consumer trends or are specific to the Labubu phenomenon.

Second, another limitation of this study is that the data collection spans the entire product lifecycle (Levitt, 1965) of the trend, from its initial emergence to the stage where engagement had largely declined. This approach was chosen to capture the full diffusion process and to understand both why individuals initially participate in rapidly emerging trends and why engagement continues even after the trend has passed its peak. While this provides a comprehensive perspective on the trend's development and persistence, it may limit deeper insights into the specific factors associated with the rapid rise in engagement during the earliest stages of the trend as research shows that different variables matter at different stages of diffusion (Wejnert, 2002). Future research could therefore adopt a narrower temporal focus by examining only the period from the trend's emergence to its peak. Such an approach could generate more detailed insights into the factors related to rapid traction and intense early engagement, as well as explain why certain trends spread exceptionally quickly during their initial diffusion phase.

Third, the sampling procedure relied on the manual selection of Reddit posts identified through Google Advanced Search. Although efforts were made to include a diverse range of discussions and perspectives related to the Labubu phenomenon, the resulting sample may not fully represent the broader population of Labubu-related conversations on Reddit. In addition, the choice of Reddit as the platform for analysis constitutes a further methodological limitation. Reddit was chosen because it encourages more in depth reflection and discussion (Reddit Inc., 2026), which was beneficial for examining discussion topics and emotional expressions. However, this choice may limit the generalizability of the findings to other platforms and partly reflect platform-specific social dynamics rather than broader patterns of consumer behavior. For instance, TikTok has the highest engagement levels among social media platforms (Zote, 2026). In addition, TikTok was the platform where the Labubu phenomenon largely went viral (Murray, 2025) and is widely recognized for its ability to continuously drive product trends (Loper, 2023). Therefore, replicating this study on TikTok, either in relation to Labubu or another consumer product trend, could contribute to future research by exploring the factors that drive trends on a platform that consistently generates these types of viral outcomes. It could also be examined whether similar relationships emerge across platforms characterized by different user demographics and interaction mechanisms.

Fourth, upvotes were operationalized as a measure of engagement in this study because they represent a central interaction mechanism on Reddit. Through the platform's upvote and downvote system, discussions that receive more attention and interaction become more visible to other users (Reddit Inc., 2026). However, engagement on Reddit can take several different forms, meaning that this operationalization did not capture all aspects of user engagement. Future research could therefore examine alternative measures, such as comment replies, which may reflect engagement that is more closely tied to discussion and interaction rather than simply expressions of liking or resonance. This distinction is important, as previous research suggests that likes, comments, and shares represent different types of engagement driven by different underlying motivations (Kim & Yang, 2017).

Fifth, engagement on social media platforms is influenced by various factors (Sabate et al., 2014). The number of upvotes received may be influenced not only by the content itself, but also by exposure-related factors such as the age of a post or comment, the subreddit in which it was published, whether the entry was a post or comment, the timing of publication, and the visibility of the surrounding discussion thread. These factors were not controlled for in the present study and may therefore have introduced additional variation into the engagement measure. Future research could incorporate such variables as controls to isolate more precisely the effects of topics, sentiment, and emotions on consumer engagement.

Sixth, another limitation concerns the NLP techniques employed in the study. While NLP techniques such as sentiment/emotion analysis and topic modeling are well-established methods for analyzing large-scale text data (KS, 2024; Tuan et al., 2024; Huang et al., 2025; Aslam et al., 2022), they have certain limitations, including challenges in capturing nuanced language (e.g., sarcasm) (Joshi et al., 2017). Thereby, there could be inconsistencies in interpreting social media communication with use of sarcasm, irony, slang, memes, and culturally specific references. While manual checks of selected entries were conducted to assess the reasonableness of the classifications, some degree of misclassification may nevertheless remain. Future research could further combine automated techniques with manual coding procedures to further validate and refine the findings.

Last, the findings identify associations between topics, sentiment, emotions, and engagement rather than causal relationships (Ejima et al., 2016). Although certain discussion characteristics were associated with higher or lower levels of engagement, it cannot be determined whether these characteristics directly caused the observed engagement patterns. Future research could employ experimental designs or longitudinal approaches to investigate causal mechanisms more directly.

6. References

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7. Appendix

Appendix 1 – Data and Code Availability

The dataset used in this thesis is not publicly available but may be obtained by contacting the authors.

The Python scripts are available here: https://colab.research.google.com/drive/19pcgScEXzggVleoKmTl6wpkaCpTptKOf#scrollTo=jIr2Gk95iHWo.

Appendix 2 – AI Disclosure

Artificial intelligence (AI)-based tools were used during the research and writing process of this thesis. ChatGPT was used for language improvement, refinement of text flow, and structural suggestions. Claude was used for figure generation. DeepL was used to translate scraped comments that were not originally in English. SciSpace and Perplexity were used in the initial stages of the research process to gain a broader understanding of the research area and identify relevant literature and concepts. Gemini, integrated with Google Colab, was used to support parts of the coding process in Python, including code development and the identification and correction of coding errors. Although Gemini assisted in generating and refining code, all methodological decisions were made by the researchers, and all code was subsequently reviewed and verified to ensure its accuracy and appropriate implementation.

All analyses, interpretations, critical evaluations, and final written content were reviewed and validated by the authors, who take full responsibility for the content of this thesis.