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Research Article

Let the Customers Speak Their Hearts Out: The Role of Verbosity and Emotions in Online Viewer-to-Viewer Engagement

Fahad Mansoor Pasha ¹, Fatima Habib ², Komal Kamran ², Akbar Azam ², Zeeshan Ali,³ and Dildar Hussain ⁴

¹Faculty of Business Administration, Lahore School of Economics, Lahore, Punjab, Pakistan

²FAST School of Management, National University of Computer & Emerging Sciences, Lahore, Punjab, Pakistan

³Oxford Brookes Business School, Oxford Brookes University, Oxford, UK

⁴School of Management, Rennes School of Business, Rennes, France

Correspondence should be addressed to Komal Kamran; komal.kamran@nu.edu.pk

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This study examines the combined impact of emotions, emojis, and verbosity on online viewer-to-viewer engagement, focusing on their interaction in shaping engagement behaviors. Using sentiment analysis with the Syuzhet package in R Studio and logistic regression on over 15,000 YouTube comments from the “YouTube Ads Leaderboard: 2021 Cannes Edition,” this research identifies key drivers of replies to initial comments. Results reveal that verbosity significantly enhances engagement, while emojis generally diminish it. Arousal-inducing emotions, such as anticipation and anger, positively influence engagement but are moderated by comment length. These findings extend the understanding of digital engagement by integrating textual, emotional, and stylistic elements into a unified framework. The study provides actionable insights for marketers to optimize user interaction and opens avenues for further exploration of engagement strategies across digital platforms.

Keywords: emojis; emotions; social media; verbosity; viewer-to-viewer engagement

Summary

- The current study deals with online viewer-to-viewer engagement, investigating the interactive role of emotions, emojis, and verbosity in driving viewer-to-viewer engagement—a critical part of viral marketing and online opinion leadership activity that the existing marketing literature overlooks.
- Results show the importance of certain emotions and verbosity (and the lack of impact of emojis) in driving online viewer-to-viewer engagement.
- Managers and practitioners will find the results useful in driving social media engagement.

1. Introduction

Online viewer-to-viewer engagement has become increasingly vital in social media marketing, where discussions among viewers can significantly influence product perceptions and purchasing decisions. Despite its importance, research into the combined effects of various factors influencing viewer-to-viewer engagement remains underexplored. Prior studies focus on emotions, verbosity, or emojis individually, but there is a critical gap in understanding how these factors interact to shape engagement behaviors. This study is the first to empirically examine these combined effects, addressing a key gap in digital communication research.

The significance of studying viewer-to-viewer engagement stems from its role in shaping consumer decisions. Viewers often engage with others in forums, chat rooms,

blogs, and especially in the comment sections of platforms like YouTube. Positive interactions between viewers can encourage others to engage with a brand or product, as previous research on word of mouth (WOM) has shown [1]. However, no prior research has investigated the simultaneous effects of textual elements (verbosity), symbolic representations (emojis), and emotional tone on audience engagement. While Mladenović et al. [2] found that emojis enhance emotional engagement in hedonic product campaigns, they did not explore how emojis interact with verbosity or emotional tone. Similarly, Wang et al. [3] showed that emotional emojis increase engagement in aesthetic content, whereas semantic emojis perform better in promotional content, but their study excluded verbosity as a factor. Dolan et al. [4] demonstrated that emotional appeals drive passive engagement behaviors but did not analyze the role of emojis or verbosity in shaping engagement. This lack of empirical investigation limits our understanding of how these factors interact to influence replies in online comment sections.

To address this gap, this study poses the following research question: *How do emotions, verbosity, and emojis interact to influence viewer-to-viewer engagement in social media comments?* By empirically examining these three factors in tandem, our research provides unique insights into how textual, emotional, and symbolic elements work together to drive engagement behaviors.

Existing research on viewer engagement largely focuses on emotions. For instance, between 2002 and 2013, 340 emotion-related articles were published, many of which explored the relationship between emotions and consumer behavior [5]. However, emotions alone do not fully explain viewer-to-viewer engagement. Studies such as those by Berger and Milkman [6] highlight the role of high-arousal emotions like anger and anticipation in driving engagement but fail to examine how these emotions interact with verbosity or emojis. Similarly, Hollebeek et al. [7] explore the role of emotions in consumer brand engagement but exclude emojis and verbosity, limiting their analysis to emotional factors alone. Other studies, such as Moe and Schweidel [8], analyze positive and negative reviews without addressing the interaction between emotions, verbosity, and emojis. By building on this existing literature and addressing these gaps, our study provides an empirical examination of how textual, emotional, and symbolic elements combine to drive engagement.

Recently, Mladenović et al. [2] demonstrated that emojis have a mixed impact on purchase intentions for hedonic products, with their effectiveness being mediated by positive affect. While emojis may reduce engagement in informational content, they have been shown to enhance emotional responses in hedonic product campaigns, emphasizing the importance of context in emoji use. However, the role of verbosity and its interaction with emotions was not explored. Similarly, Wang et al. [3] found that emotional emojis increased engagement in aesthetic content, whereas semantic emojis performed better in promotional content, but verbosity was not included in their analysis. Our study extends these findings by integrating verbosity as a key textual factor, exploring its interaction with emotions and emojis in driving viewer replies.

McShane et al. [9] showed that emojis can enhance engagement by increasing perceptions of playfulness; however, this study focused on Twitter, where limited character counts drive brevity and may not directly apply to platforms like YouTube, where longer text and verbosity play a larger role. Additionally, Dolan et al. [4] found that rational appeals on social media facilitate both active and passive engagement, while emotional appeals tend to drive passive engagement, despite the inherently interactive nature of digital media. This study, however, does not consider the interaction between emojis, emotions, and comment length. Our research bridges this gap by analyzing how these factors combine to influence engagement, specifically focusing on YouTube, a platform where verbosity and emotional content coexist in user comments.

Other works, like Dessart [10], focus on social media engagement as a multidimensional construct influenced by factors such as product involvement, attitudes toward the community, and online interaction propensity but do not address the impact of emojis or verbosity. Similarly, Wang and Liu [11] examine the effects of privacy and culture on online engagement but do not investigate the role of emojis or comment length in these contexts. Our study advances these discussions by focusing on viewer replies as a tangible metric of engagement and examining how textual and emotional factors drive these interactions.

In sum, although some previous studies examine emotions and verbosity separately (e.g., [12, 13]), no study has investigated the combined effects of emotions, emojis, and verbosity on online viewer-to-viewer engagement. By leveraging an empirical dataset of 15,000 YouTube comments, our study provides a unique contribution to the literature by offering new insights into how these factors interact.

This study addresses the gap by investigating the combined effects of emotions, verbosity, and emojis on viewer-to-viewer engagement in online comment sections. By focusing on the interplay of these three factors, we aim to build on existing research and provide new insights into how these elements work together to influence engagement. Specifically, we adopt a quantitative approach, analyzing 15,000 YouTube comments from the “YouTube Ads Leaderboard: 2021 Cannes Edition” using sentiment analysis and logistic regression, to identify the factors driving replies as a measure of engagement.

Our findings show that verbosity plays a central role in driving engagement, with longer comments significantly increasing the likelihood of replies. Arousal-inducing emotions, such as anticipation and anger, also enhance engagement, particularly when combined with shorter, more concise comments. Interestingly, we find that the use of emojis tends to reduce the likelihood of replies, contradicting the common assumption that emojis enhance emotional expression and engagement. These findings contribute to a deeper understanding of viewer engagement, providing actionable insights for marketers on fostering meaningful interactions on social media platforms.

In the following sections, we outline the theoretical background, detailing relevant literature on emotions, verbosity, and emojis. We then present our hypotheses and methodology,

followed by an analysis of the results. Finally, we discuss the theoretical and managerial implications of our findings and suggest avenues for future research.

2. Theoretical Background

2.1. Engagement. Engagement is a broad term. Engagement involves multiple components, such as involvement, interaction, intimacy, and influence [14]. Viewer engagement reflects a viewer's cognitive, emotional, and behavioral investments in a brand [15], with higher engagement increasing purchase behaviors and increasing brand equity [7]. In social media, viewer engagement can be measured in several key ways, such as likes and comments [16]. Likes represent the lowest engagement (requiring a single click that is effortless and reflexive), with the meaning behind the action remaining a mystery. Comments, on the other hand, require more physical and cognitive effort, such as reading the post and creating a response.

To increase viewer engagement in online environments, the comments posted are extremely important. Positive rating environments encourage posting, whereas negative rating environments discourage posting, especially among low-involvement individuals [8]. As a result, the posting population is skewed in favor of negative comments, which can bias the overall opinion of the product. Companies can suffer negative WOM, creating negative business consequences, such as decreased brand equity. Given the importance of viewer engagement in online environments, the role of emotions, emojis, and verbosity needs to be explored.

2.2. Emotions. Emotions are mental states of readiness that arise from cognitive appraisals of events or thoughts [17]. The underlying evaluation of a situation—such as the desirability, the extent of control, coping potential, and certainty—combines to create emotions and influences consumer behavior [18]. The circumstances of an individual can cause emotions that lead to behaviors. For example, Brown et al. [19] show that when salespersons achieve performance goals, positive emotions are created that lead to greater effort. Although emotions are not long-lasting (moods last longer), emotions have a high intensity and influence the decision-making process, satisfaction, and postpurchase behaviors, especially for high-involvement services (see [18, 20]). Since negative emotions involve more extensive information processing, negative emotions can cause dissatisfaction for long periods [21].

In online environments, viewer emotions' can influence overall product evaluations. Viewers with positive emotions evaluate stimuli—such as cars and possessions (regardless of hedonic or utilitarian products; see [22])—positively, while viewers with negative emotions evaluate stimuli negatively. Furthermore, viewers can base evaluations of a stimulus based on the affective states being experienced, since affective states are considered reactions to a stimulus. For instance, if ice cream ads and viewer comments make other viewers feel good, then the viewer likes the ice cream [17].

Importantly, emotions can be induced with minimal effort. For instance, shopkeepers can increase a customer's level of pleasure and arousal—such as with in-store music

and in-store aroma—which further increases customer satisfaction and loyalty [23]. In online environments, viewer comments can induce positive or negative emotions with great ease. Positive or negative emotions can be associated with product use and recalled later [24], especially for viewers with high affect intensity [25]. Given the importance of emotions, the question that arises is how do emotions influence online viewer-to-viewer engagement?

2.3. Emotions and Online Viewer-to-Viewer Engagement. Several studies related to viral marketing showcase the role of emotions in online viewer engagement, showing how a myriad of strategies, ranging from scarcity and personalization of messages to humor and outrage, influence viewer engagement (see [26–28]). For instance, Libert and Tynski [29] show that while emotions are necessary for generating sharing behavior, a variation in the use of emotions is necessary to avoid boredom. Viewers respond to communications that contain more positive emotions and less negative emotions. However, negative emotions do not harm ad-sharing behavior [30]. Negative emotions that evoke anticipation (see [31]) and surprise generate viewer interest and are closely related to curiosity, amazement, interest, astonishment, and uncertainty. In fact, perceived risk (e.g., anxiety) increases the amount of eWOM (electronic word of mouth) [32].

Berger and Milkman [6] also show that positive marketing communications generate more sharing behavior when compared to negative marketing communications, although affect-laden marketing communications are more likely to generate viewer engagement than non-affect-laden marketing communications (i.e., marketing communications that have neither positive nor negative emotions). Tellis et al. [33] also show that positive emotions involving amusement, excitement, inspiration, and warmth increase sharing. Importantly, awe-inspiring (positive) marketing communications are more likely to be virally shared, while sadness-inducing (negative) marketing communications are less likely to be virally shared.

However, several negative emotions—such as anxiety and anger-inducing emotions—are more likely to engage viewers and be shared. Berger and Milkman's [6] study shows that marketing communications that contain high-arousal emotions (such as awe, anger, and anxiety) are more likely to engage viewers and be shared with other viewers. On the other hand, marketing communications that contain low-arousal or deactivating emotions (such as sadness) are less likely to engage viewers (see [34]).

The literature on viral marketing shows the importance of arousal-increasing emotions and the use of simple cues and heuristics in processing viral marketing messages (consumers mostly seek fun and entertainment and rely on simple cues and heuristics to process information, consistent with the elaboration likelihood model (ELM); see [35]). Based on the literature, we can hypothesize that comments that involve arousal-increasing emotions—such as anger, anticipation, anxiety, and surprise—will increase viewer-to-viewer engagement.

H1: Comments that involve arousal-inducing emotions will increase viewer-to-viewer engagement.

Several factors can engage viewers online and allow viewers to better express themselves, such as the verbosity of comments and the use of emojis. The role of verbosity and emojis is discussed next.

2.4. Emojis and Viewer Engagement. Companies and brands use emojis to convey emotions. Emojis are used to express complex emotions (such as fear, surprise, and embarrassment), inform opinions, provide information, and ask for input [36]. Emojis can humanize a message, increasing message recall [37]. When combined with text-based messages, emojis reduce the possibility of multiple interpretations, increasing the accuracy of communications [38]. Emojis can influence perceptions. For instance, emojis with a dark-brown skin tone can create perceptions of inclusiveness for conservative brands [39]. When used in postpurchase communications, emojis lessen customers' anxiety and increase satisfaction and product liking [40]. Similarly, emojis increase purchase intentions for future-oriented buyers (due to feelings of excitement) [41]. However, the impact on viewer-to-viewer engagement is debatable.

Zhang et al. [42] show that emojis do not increase online engagement or appreciation in microblogs. The impact observed is similar for both the western participants and the eastern participants (i.e., the effect is consistent across cultures). Li and Xie [43] show that on Twitter, the presence of emojis increases the obtrusiveness of a tweet, decreasing the number of retweets received. However, McShane et al. [9] show that emojis in tweets increase viewer engagement—by creating perceptions of playfulness—with more emojis leading to more likes, shares, and retweets. Emojis that contain asymmetric facial expressions receive more favorable customer evaluations—especially from consumers with higher emotional sensitivity—due to higher perceptions of human expression resemblance and emotional expression [44].

It is important to note that while emojis bring benefits, the benefits are only expected under communal relationship conditions, such as in one-to-one company–customer relationships [45]. When communicating to a larger audience, such as on a company's social media webpage, the audience is large, reducing the chances that the receivers attribute emotional expression as personally directed.

Based on the literature, we can hypothesize that emojis are likely to increase emotional expressions and perceptions of perceived playfulness. When viewers communicate with each other, emojis are unlikely to be seen as communications directed at a mass audience. Rather, the emojis are likely to be seen as emotionally directed to other viewers. Hence, we expect emojis to increase viewer-to-viewer engagement.

H2: Greater use of emojis will increase the likelihood of viewer-to-viewer engagement.

Next, the role of verbosity in viewer-to-viewer engagement is discussed.

2.5. Verbosity and Viewer Engagement. Verbosity refers to expressing ideas in a greater amount of words. Several studies show that verbosity influences behavior. For instance, Kornish and Jones [13] show that ideas expressed in a

greater amount of words are rated higher, especially in terms of creativity, due to perceptions of novelty and usefulness. As the effort required to read increases and less familiar and more novel ideas are explored, perceptions of complexity are created. Aaker [46] also expounds on how greater quantity or quality improves evaluations of capability. For instance, bigger speakers give better sound.

In terms of marketing, Sela and Berger [47] show that more verbose product descriptions raise perceptions of the capability or usefulness of the ideas described. Petty and Cacioppo [48] show that a higher number of arguments—similar to description length—create a more-is-better heuristic. When subjects are not highly invested in a topic—similar to the case of viewers who engage in social media for pleasure and fun—heuristic processing increases and the persuasiveness of the length of the argument increases. An increase in description length [49] and information provided [50] increases complexity, which can be both a source of perceived novelty [51] and uncertainty [52]. As mentioned previously when discussing viral marketing, uncertainty creates anxiety which increases viewer-to-viewer engagement and ad-sharing behavior. By increasing novelty, verbosity increases hedonistic pleasures, which increase the chances of sharing online content (see [12]).

On the other hand, Li and Xie [43] show that verbosity does not increase viewer-to-viewer engagement. For instance, an increase in the length of a tweet (on Twitter) increases the obtrusiveness of the tweet. Similarly, the length of a post does not affect viewer-to-viewer engagement on Instagram. However, Twitter and Instagram likely focus on being brief and precise. Verbosity may not increase engagement for such platforms. Given the role of verbosity in increasing novelty, uncertainty, usefulness, and complexity, we hypothesize that verbosity will increase viewer-to-viewer engagement.

H3: An increase in verbosity in a comment will increase viewer-to-viewer engagement.

The marketing literature on verbosity is limited. However, numerous marketing literature based on the narrative theory and the storytelling theory exists about using numerous words to express ideas, although the stream of literature focuses on using stories, drama, and plots (see [53, 54]). For instance, average shares and views are higher for videos with fully developed stories (especially when using first-person narration; see [55, 56]). Storytelling also helps in increasing sales in B2B markets [57]. However, in the current study, storytelling or narration is not in focus. Rather the focus is on verbosity. Verbose comments likely contain some stories, although stories or narrations are not the focus of the study.

An important point to note is that verbosity is likely to have an interaction effect with emotions and emojis since greater comment length allows viewers to express greater emotions and opinions. Hence, we hypothesize that verbosity will increase the likelihood of emotions and emojis in increasing viewer-to-viewer engagement.

H4: When verbose comments contain (1) arousal-increasing emotions and (2) emojis, viewer-to-viewer engagement will increase in the form of replies.

After having discussed the hypotheses, an empirical analysis follows.

3. Overview of the Study

In the current study, we are going to investigate the likelihood of emotions, verbosity, and emojis in increasing the higher form of online viewer-to-viewer engagement: replies to other viewers' comments (see [16]). The current study considers the top 10 ads from "YouTube Ads Leaderboard: 2021 Cannes Edition"¹. The ads are the most popular global videos on YouTube since the year before 2021. The ads are chosen because they attract large audiences, with wide variation in comments (e.g., length of comments, absence or presence of comments), emojis (e.g., absence or presence of emojis), and emotions (e.g., viewers can be happy or sad).

The titles of the top 10 ads in terms of viewership, from first to the last, are "ViIsHere – Launch," "Feel the Rhythm of KOREA: JEONJU," "No Drama," "LOST & CROWNED|A Clash Short Film," "OPPO F17 Pro Diwali Edition|#BeTheLight To Spread The Light," "Amazon's Big Game Commercial: Alexa's Body," "The Norms of Life," "Hyundai x BTS|For the Earth 60 sec," "It Already Does That," and "You Can't Stop Us."

From the 10 ads, data was gathered for four ads. Comments for "ViIsHere – Launch" are disabled. For "Feel the Rhythm of KOREA: JEONJU," the comments are mostly in Korean, creating difficulties in coding and carrying out sentiment analysis. The comments for "The Norms of Life" are in Egyptian, creating coding and sentiment analysis difficulties. The video for "It Already Does That and You Can't Stop Us" is set to private, disallowing us to analyze the comments. Since the "LOST & CROWNED|A Clash Short Film" is a short film, rather than an ad, comments are excluded from the analysis.

For the four ads that are selected in the study, "No Drama" (uploaded May 4, 2021) has 52,811,030 views and 878 comments, "OPPO F17 Pro Diwali Edition|#BeTheLight To Spread The Light" (uploaded October 19, 2021) has 74,215,002 views and 2960 comments, "Amazon's Big Game Commercial: Alexa's Body" (uploaded February 2, 2021) has 78,492,224 views and 8239 comments, and "Hyundai x BTS|For the Earth 60 sec" (uploaded April 22, 2020) has 105,759,723 views and 5188 comments. Hence, "Hyundai x BTS|For the Earth 60 sec" has the highest number of views, while "Amazon's Big Game Commercial: Alexa's Body" has the highest number of comments.

For analysis, comments were extracted from the YouTube pages of the four ads on March 29, 2022. Along with the comments, the name of the commenter, the comment content, the time of the comment, replies to the comments, and the number of likes for each comment were extracted. The number of replies to a comment—reply count—acts as the measure of viewer-to-viewer engagement in the current study.

We acknowledge certain limitations of the dataset. First, the dataset is platform-specific, focusing solely on YouTube, which may limit the generalizability of findings to other platforms such as Instagram or Twitter. Second, the timeframe of data collection (2022 for ads published in 2021 or earlier) does not capture potential shifts in user engagement behavior over time. However, these limitations are mitigated by the large sample size, which allows for reliable and robust pattern analysis within the selected context.

3.1. Data Preprocessing. To prepare the data for sentiment analysis, preprocessing and cleaning are performed. First, the extracted comments are cleaned by removing any irrelevant features such as URLs, HTML tags, and special symbols, to retain textual content only. Tokenization is then performed to break down the comments into individual words. Common stopwords (e.g., "and," "the," and "of") that do not contribute significantly to the sentiment are removed. Finally, words are reduced to their root forms through lemmatization for effective sentiment analysis.

3.2. Quantitative Versus Qualitative Methods. The large-scale nature of the dataset necessitated the use of quantitative methods, which are well suited for identifying statistically significant patterns across thousands of data points. While qualitative approaches such as thematic analysis could provide deeper insights into the contextual nuances of individual comments, they are less effective for generalizable, large-scale analyses like the one conducted here. Quantitative methods also ensure replicability, a key strength of this study, allowing future researchers to expand or replicate the findings systematically.

3.3. Sentiment Analysis. To analyze the emotions embedded in each comment, sentiment analysis was conducted using the Syuzhet package in R Studio [58]. Syuzhet was selected for its ability to extract narrative structures and detect emotional arcs within textual data, making it highly suitable for analyzing viewer comments. Compared to other sentiment analysis tools, such as TextBlob or VADER, Syuzhet offers enhanced capabilities by incorporating multiple sentiment dictionaries (e.g., NRC Emotion Lexicon) and capturing fine-grained emotional nuances. This feature allows for the detection of subtle emotional shifts across a series of comments, which is essential for understanding how emotions impact viewer-to-viewer engagement.

Developed by the Natural Language Processing group at Stanford University, the Syuzhet package includes four sentiment dictionaries and advanced sentiment extraction features. Its machine learning algorithms categorize comments into one of eight emotions: anger, anticipation, disgust, fear, joy, sadness, surprise, and trust. The flexibility of the package also enables future researchers to replicate the analysis with different datasets or parameters, enhancing the replicability of this study. The primary goal of this sentiment analysis is to identify the emotions present in comments that could influence viewer-to-viewer engagement, particularly their likelihood of receiving a reply (e.g., as discussed by [6]).

3.4. Verbosity. To account for the verbosity of the comments, the number of characters is counted in each comment after removing punctuations, commas, exclamation marks, and html page elements. The variable—comment length—shows the number of characters in a comment.

3.5. Emojis. To see how the use of emojis influences viewer-to-viewer engagement, the number of emojis in each comment is counted using the package "emoji" on R studio. Next, we create empirical models using the data gathered.

4. Empirical Analysis

Ten percent of the comments contain words related to anger, 15% of the comments contain words related to anticipation, 8% of the comments contain words related to disgust, 9% of the comments contain words related to fear, 19% of the comments contain words related to joy, 9% of the comments contain words related to sadness, 8% of the comments contain words related to surprise, and 15% of the comments contain words related to trust. Hence, the majority of the comments contain words related to joy, anticipation, and trust, with the least proportion of comments containing words related to disgust or surprise. Furthermore, 26% of the comments contain emojis. Table 1 shows the correlations between the eight emotions, reply count (i.e., viewer-to-viewer engagement), and comment length (i.e., verbosity).

Table 1 shows that likes and reply count have a high correlation (0.66). Anger and anticipation seem to be moderately correlated (0.42). High correlations are observed between disgust and anger (0.78), sadness and anger (0.68), and fear and anger (0.74). Comment length is highly correlated with anger (0.61). Anticipation is highly correlated with comment length (0.61). Joy is highly correlated with anticipation (0.71) and trust (0.76). Trust (0.73) and fear (0.73) are highly correlated with comment length. However, the number of emojis in comments is not correlated with likes, reply count, or any of the eight emotions. Surprisingly, likes or reply count are not correlated with emotions.

The correlations show an absence of a strong relationship between the eight emotions, emojis, and reply count. However, correlations show a linear relationship. Possibly, the relationship between the eight emotions, emojis, and reply count is nonlinear. We use logistic regression analysis to consider nonlinear relationships.

4.1. Logistic Regression. The number of replies—reply count—is coded as a dummy variable showing the probability of a reply or a no reply. The results show that a total of 13% of the comments (1493 comments) received a reply, compared to 87% of the comments (9974 comments) that did not receive a reply. Furthermore, 96% of the comments received no likes. The difference between the percentage of comments that receive a reply or a like shows that comments that receive a reply do not always receive likes.

For verbosity, a new dummy variable is created—comment length. Options show whether comments have a length that is less than or equal to the average comment length of 52.4 characters (excluding punctuations and emojis) or greater. Around 31% of the comments are greater than the average comment length.

We follow a hierarchical model approach. Model 1 in Table 2 shows a basic model excluding the ad category or interactions. Model 1 includes the eight emotions, comment length, and the number of emojis with reply count as the dependent variable. Model 2 builds on Model 1 by controlling the impact of the ad categories (with Amazon Alexa as the base ad category). Model 3 builds on Model 2 by adding

interactions of the eight emotions and the number of emojis with the dummy variable—comment length.

Model 1 shows that anger, sadness, and a higher comment length increase the likelihood of receiving a reply. The presence of emojis, fear, and joy decreases the likelihood of receiving a reply. In terms of magnitude, comment length has approximately three times the magnitude compared to anger in increasing the likelihood of a reply. Model 1 and Model 2 show that while the OPPO F17 Pro ad increases the likelihood of a reply, the Hyundai BTS ad decreases the likelihood of a reply. Compared to Model 1, the same variables are significant in Model 2, except that the number of emojis loses significance and the coefficients on comment length and anger increase.

When interactions between comment length, the number of emojis, and the eight emotions are included in Model 3, anger increases the chances of a reply when the comment length is above average. On the other hand, anticipation and sadness increase the chances of a reply when the comment length is below average. The likelihood of a reply decreases when anticipation, fear, and joy are present in comments with above-average comment length. A lower AIC (Akaike information criterion) value for Model 3 (7870.2) compared to the AIC value for Model 2 (7887.5) and Model 1 (8616.7) shows that Model 3 fits better [59].

In addition to AIC, the likelihood ratio test is a measure of fit for the logistic regression. The likelihood ratio test compares the intercept-only model with the model with regressors [60]. The null hypothesis states that the regressors do not have any significant impact. However, the likelihood ratio test in Model 2 is rejected at the 0% level, showing that the variables in Model 2 are jointly significant in predicting the likelihood of reply. Next, the likelihood test ratio for Model 3 with interactions compares a model with the interactions and a model without the interaction, performing a chi-square test for -2 times the difference of the log-likelihood values [61]. The null hypothesis—that the regressors in Model 3 do not jointly predict the probability of reply—is rejected at the 5% significance level, showing that Model 3 is significant.

4.2. Marginal Impacts. We cannot simply interpret the likelihood of a reply based on the output in Model 3. We need to find the marginal impact on the likelihood of reply based on the logarithmic CDF (cumulative distribution function) [62]. The probability of reply is conditional on the specific values that are selected for the multiple regressors. To isolate the impact of each variable on the likelihood of a reply, the values of all other variables in Model 3 are set to 0.

In terms of the ad categories, the likelihood of a reply is 3.1% when the Hyundai ad category is selected. However, the likelihood of a reply increases to 6.7% when a non-Hyundai ad category is selected, showing that the Hyundai ad category decreases the likelihood of a reply by 3% (the impact appears to be quite small). However, in the case of the OPPO F17 Pro ad, the likelihood of a reply increases to 25.5% compared to a likelihood of a reply of 6% for a non-OPPO F17 Pro ad category. Hence, the OPPO F17 Pro ad has a high impact on increasing the likelihood of a

TABLE 1: Correlations between the eight emotions, reply count, and comment length.

	1	2	3	4	5	6	7	8	9	10	11
1. Likes											
2. Reply count	0.66										
3. Anger	0.03	0.05									
4. Anticipation	0.01	0.04	0.42								
5. Disgust	0.01	0.03	0.78	0.39							
6. Fear	0.01	0.02	0.74	0.58	0.68						
7. Joy	0.00	0.02	0.39	0.71	0.36	0.49					
8. Sadness	0.02	0.03	0.68	0.43	0.68	0.75	0.42				
9. Surprise	0.03	0.04	0.38	0.61	0.32	0.42	0.62	0.38			
10. Trust	0.01	0.02	0.50	0.76	0.47	0.64	0.76	0.50	0.59		
11. No. of emojis	-0.00	0.01	-0.01	-0.02	-0.01	0.00	0.01	-0.01	-0.01	-0.01	
12. Comment length	0.02	0.04	0.61	.61	0.56	0.73	0.58	0.59	0.43	0.73	0.04

reply. When the comment length is below or equal to the average comment length (52.4 characters), the likelihood of a reply is only 6.7%. However, when the comment length is above average, the likelihood of a reply increases to 22.4%.

When comments contain anger and have an above-average comment length, the likelihood of a reply is 10.3% compared to a likelihood of 6.7% when anger is not present in a comment with an above-average length. Anticipation influences the likelihood of a reply when the comment length is either below average or above average. When the comment length is below average, the likelihood of a reply increases to 11.2% when a comment contains anticipation compared to a likelihood of a reply of 6.7% when anticipation is not present. When the comment length is above average, the likelihood of a reply is 5.3% when anticipation is present. However, when anticipation is not present, the likelihood of a reply increases to 6.7%.

When fear is present in a comment with a below-average length, the likelihood of a reply is 4.1%. However, the likelihood of a reply increases to 6.7% when fear is absent. When joy is present in a comment with a below-average length, the likelihood of a reply is 3.8%. When joy is absent from a comment with a below-average length, the likelihood of a reply increases to 6.7%. When a comment with a below-average length contains sadness, the likelihood of a reply increases to 15.4% compared to a likelihood of a reply of 6.7% when sadness is absent. Figure 1 summarizes the methodology of the study along with preliminary observations.

5. Discussion

Our results demonstrate significant relationships between the factors of emotions, verbosity, and emojis in influencing online viewer-to-viewer engagement. The majority of comments in our dataset reflect positive emotions such as joy, anticipation, and trust, while disgust and surprise are less frequent. We found that anger and sadness are highly correlated with comment length, suggesting that longer comments often stem from negative emotions. These results align with previous studies showing that arousal-inducing

emotions like anticipation and anxiety play a critical role in driving engagement [31, 32].

Across all the comments analyzed, only 13% received a reply, while 4% received a like. However, logistic regression models reveal that certain factors significantly increase the likelihood of receiving a reply. Model 1, which included the eight emotions, comment length, and the number of emojis, shows that anger, sadness, and longer comment length increase the likelihood of a reply. This supports Hypothesis 1 (that arousal-inducing emotions drive engagement) and Hypothesis 3 (that verbosity enhances engagement). The presence of emojis, fear, and joy decreased the likelihood of a reply, leading to the rejection of Hypothesis 2, which predicted that emojis would increase engagement.

Model 2, which controls for the effect of the ad categories, maintains the significance of these relationships. Notably, the OPPO F17 Pro ad increases the likelihood of receiving a reply, while the Hyundai BTS ad decreases it. This demonstrates that ad content and context may interact with viewer responses, influencing how engagement factors play out across different campaigns. Model 3, which introduces interaction effects between comment length, emojis, and emotions, provides further nuance. For comments with above-average length, anger significantly increases the likelihood of a reply by 3%. Sadness and anticipation increase engagement when the comment length is below average, with anticipation increasing the probability by 4.5% and sadness by 7.8%. Interestingly, when anticipation appears in longer comments, the likelihood of receiving a reply decreases by 0.6%, suggesting that brevity enhances the impact of anticipation. Additionally, when fear and joy appear in longer comments, the chances of a reply decrease by 2.6% and 2.9%, respectively. These results validate Hypothesis 4, highlighting that verbosity interacts with emotions to drive engagement, particularly for arousal-inducing emotions.

Our findings confirm and extend the existing literature. Studies such as Milkman and Berger [63] have shown that high-arousal emotions like anger and anticipation drive sharing behavior. Our results build on this by demonstrating that these emotions, particularly when paired with verbosity,

TABLE 2: Impact of emotions, verbosity, and emojis on the probability of a reply.

Dependent variable: probability of receiving a reply	Model 1	Model 2	Model 3
Ad category: Hyundai BTS (base ad category: Amazon Alexa)		-0.82 (0.08)***	-0.80 (0.08)***
Ad category: no drama (base ad category: Amazon Alexa)		0.22 (0.12)	0.21 (0.12)
Ad category: OPPO F17 Pro (base ad category: Amazon Alexa)		1.53 (0.07)***	1.56 (0.08)***
Anger	0.28205 (0.11)**	0.38 (0.12)***	
Anticipation	0.17 (0.09)	0.03 (0.09)	
Disgust	-0.10 (0.12)	-0.09 (0.13)	
Fear	-0.34 (0.11)***	-0.31 (0.12)**	
Joy	-0.37 (0.09)***	-0.13 (0.10)	
Sadness	0.43 (0.10)***	0.43 (0.10)***	
Surprise	0.03 (0.11)	-0.03 (0.12)	
Trust	0.05 (0.10)	-0.03 (0.10)	
Number of emojis	-0.16 (0.06)**	-0.03 (0.06)	
Comment length (base category: below average comment length)	0.82 (0.06)***	1.22 (0.07)***	1.38 (0.08)***
Interactions			
Anger × comment length (below average)			0.13 (0.26)
Anger × comment length (above average)			0.47 (0.14)***
Anticipation × comment length (below average)			0.56 (0.16)***
Anticipation × comment length (above average)			-0.25 (0.12)**
Disgust × comment length (below average)			0.009 (0.26)
Disgust × comment length (above average)			-0.12 (0.14)
Fear × comment length (below average)			-0.51 (0.26)**
Fear × comment length (above average)			-0.23 (0.14)
Joy × comment length (below average)			-0.58 (0.18)***
Joy × comment length (above average)			0.08 (0.12)
Sadness × comment length (below average)			0.93 (0.19)***
Sadness × comment length (above average)			0.21 (0.13)
Surprise × comment length (below average)			0.08 (0.24)
Surprise × comment length (above average)			-0.09 (0.13)
Trust × comment length (below average)			0.06 (0.20)
Trust × comment length (above average)			-0.08 (0.12)
Emoji × comment length (below average)			0.09 (0.09)
Emoji × comment length (above average)			-0.16 (0.09)
Intercept	-2.18 (0.04)***	-2.54 (0.06)***	-2.63 (0.07)***
AIC	8616.7	7887.5	7870.2

***Significant at the 1% level.

**Significant at the 5% level.

significantly influence viewer-to-viewer engagement on social media. However, our findings diverge from research suggesting that emojis enhance engagement [9]. We find that emojis reduce engagement, likely because they may detract from the perceived depth or seriousness of a comment, making it less likely to elicit a response.

In contrast to our findings that emojis do not significantly increase viewer-to-viewer engagement on YouTube, recent research suggests that emojis can have a positive impact on engagement in other contexts. A study focusing on brand-related user-generated content (UGC) on Insta-

gram found that the presence of emojis is associated with a 72% increase in likes and a 70% increase in comments, but this effect is highly contingent on text properties and the type of post [64]. Emotional emojis were found to have a positive interaction effect on engagement when used in posts with positive text sentiment, while informational emojis were negatively related to engagement in the same context. These findings indicate that the impact of emojis on engagement may depend on the platform, context, and content type. Our results suggest that on YouTube, where comment interactions often focus on deeper discussions, emojis may

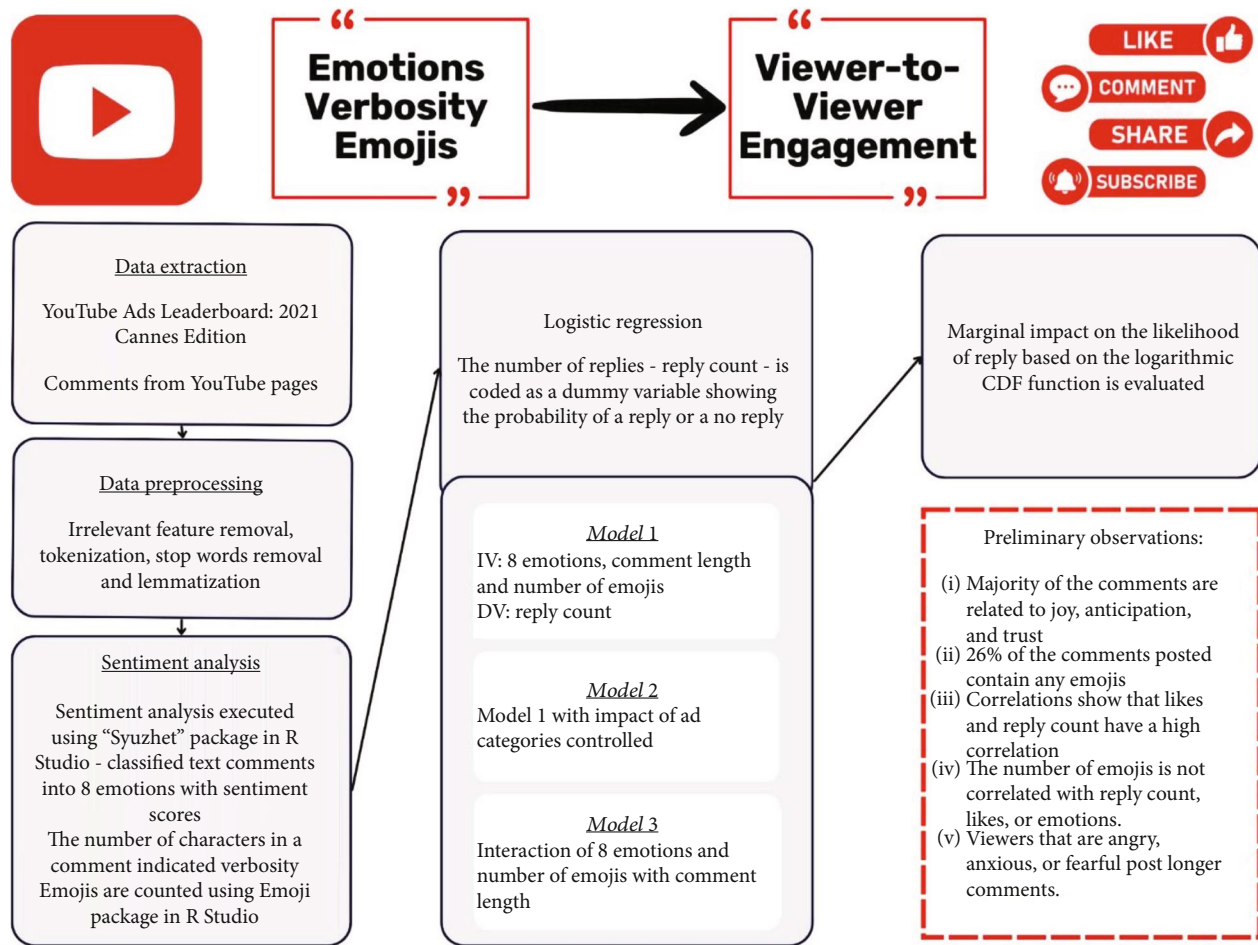


FIGURE 1: Overview of methodology and preliminary observations.

not function as effective engagement tools. However, further research should explore how platform-specific factors influence the role of emojis in social media engagement.

5.1. Theoretical Contributions. This study makes several key theoretical contributions. First, we are among the beginners to investigate the combined effects of these three factors on viewer-to-viewer engagement. Previous studies have typically examined these elements in isolation. Our findings demonstrate that while emotions and verbosity interact to drive engagement, emojis play a minimal or negative role in eliciting replies. This provides new insights into how textual elements in social media comments influence engagement, challenging conventional assumptions about the positive role of emojis in communication.

Second, our findings extend the ELM by showing that verbosity, which demands more cognitive effort, is particularly effective when paired with arousal-inducing emotions. This supports the idea that users in online comment sections engage more deeply with content that requires cognitive investment, while peripheral cues like emojis are less effective. Our findings build on prior research that applies the ELM to digital contexts (e.g., [4, 6]). While previous studies largely focus on emotional appeals, this study uniquely demonstrates how verbosity interacts with emotions to influence

viewer-to-viewer engagement. For example, prior work highlights the role of high-arousal emotions [6] but does not examine their interplay with comment length. By showing that verbosity amplifies the effects of arousal-inducing emotions like anger and anticipation, our study expands the ELM framework to account for textual complexity in online settings, providing a more nuanced understanding of how cognitive and emotional processes influence engagement.

Third, the interaction effects identified in our analysis provide valuable theoretical insights. Model 3 shows that the interaction between comment length and emotions significantly influences the likelihood of engagement, with different emotions (e.g., anticipation, anger, and sadness) having varying effects depending on the length of the comment. This interaction effect advances our understanding of how users process emotionally charged content in social media settings.

5.2. Practical Contributions. Our study makes several practical contributions to marketing managers. It is unrealistic for managers to regulate how users express themselves on social media. While managers cannot limit the use of emojis, we recommend that managers encourage deeper, more substantive comments by facilitating discussions that engage users emotionally and intellectually. Marketing teams can foster

engagement by crafting content that prompts longer, emotionally charged comments, which are more likely to elicit replies.

Rather than attempting to control emoji use, marketing managers can focus on creating an environment that encourages thoughtful engagement. For example, by posing open-ended questions or facilitating discussions around emotionally resonant topics, managers can organically drive more meaningful viewer-to-viewer interactions.

Additionally, our findings suggest that comments reflecting negative emotions, such as anger and sadness, are more likely to receive replies. While this may increase engagement, it also has the potential to create a negative tone in online discussions, which could deter potential customers. Marketing managers should ensure that moderators actively monitor and address negative comments to mitigate the spread of negative sentiments and maintain a positive brand image [8].

Finally, our results indicate that anticipation increases engagement when comments are brief and concise. Marketing managers should consider tailoring their content to create a sense of anticipation but limit the amount of information provided to maintain suspense and engagement.

While this study focuses on YouTube, the findings regarding the impact of emotions, verbosity, and emojis on viewer-to-viewer engagement may have broader implications for other social media platforms such as Twitter, Instagram, and Facebook. On Twitter, where brevity is enforced due to character limits, verbosity as a strategy may be less applicable. Instead, concise comments containing high-arousal emotions such as anger or anticipation may effectively drive engagement, highlighting the potential for emotional content to substitute verbosity on platforms with length constraints. Similarly, on Instagram, where engagement revolves around visual and aesthetic content, the role of emojis may be more context dependent. Emotional emojis paired with visually appealing posts have been shown to enhance interaction [3], suggesting that marketers could experiment with emojis as a complementary tool for boosting engagement in visually focused campaigns.

On Facebook, a platform that supports long-form posts and diverse content types, strategies encouraging verbosity align closely with this study's findings. Promoting longer, substantive comments combined with arousal-inducing emotions may help foster meaningful engagement. Nonetheless, the overall patterns of emotional engagement and user interaction observed in this study are likely to hold, suggesting that brands across platforms should tailor their engagement strategies based on the emotional and textual characteristics of UGC. Future research could explore how the interaction of these factors varies across different social media ecosystems.

6. Future Research

The current study opens many areas for further research. Firstly, the results demonstrate the role of verbosity in increasing viewer-to-viewer engagement on YouTube. However, the impact of verbosity may differ on other social

media platforms where users are expected to be more concise, such as Twitter or Instagram, which prioritize brevity. Future research can explore how verbosity affects engagement across these platforms and investigate how platform-specific behaviors influence user interactions.

While our study found that emojis did not contribute to increased engagement on YouTube, their effectiveness may vary depending on the platform and content type. Recent research on Instagram found that emojis significantly increased engagement in brand-related UGC, particularly when emotional emojis were paired with positive text sentiment [64]. These findings suggest that contextual factors, such as the type of content (e.g., promotional vs. general) and the sentiment of accompanying text, may play a crucial role in determining how emojis influence engagement. Future studies could explore the interaction between emojis and content types on YouTube and other platforms to provide a more comprehensive understanding of when and how emojis drive engagement.

Secondly, while the study shows that anger and sadness in comments tend to increase engagement, firms can mitigate the negative tone by employing customer support staff to address grievances on social media. This could help alleviate the emotional charge, encouraging positive interactions. Future studies should examine how timely intervention by brands affects the spread of negative emotions and engagement, as well as how cultural and demographic factors influence users' emotional responses and behavior in various markets and social contexts. These factors can help determine whether similar trends exist across different countries or if emotional reactions vary due to cultural differences.

Thirdly, the study reveals that anticipation increases the likelihood of a reply when the verbosity of a comment is low. As verbosity increases, engagement decreases, likely due to the diminishing thrill as more information is provided. Future research should aim to find the optimal balance of text and nontext elements (e.g., images and videos) that can maintain engagement while offering sufficient information. Additionally, examining the role of psychological moderators (e.g., individual traits like impulsivity or attention span) may provide insights into how users process emotionally charged or verbose content differently based on their personalities.

Lastly, our findings show that emojis reduce viewer-to-viewer engagement, consistent with previous studies (e.g., [43]). Future research can explore alternative ways to convey emotions concisely without emojis, such as using abbreviations, memes, or other visual elements, and how these alternatives influence engagement across different social media platforms. Furthermore, research should explore how demographic variables, such as age, gender, and cultural background, moderate the effect of these visual elements on engagement, offering a more granular understanding of how user behavior varies across different segments.

In summary, future studies should examine these findings across diverse geographic contexts, demographic groups, and periods to determine whether trends remain consistent and how external factors such as cultural norms and individual differences impact viewer-to-viewer engagement.

Data Availability Statement

The data that support the findings of this study are openly available in Mendeley Data at <https://data.mendeley.com/datasets/c74974spph/1>.

Conflicts of Interest

The authors declare no conflicts of interest.

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Endnotes

¹The videos can be found at <https://www.youtube.com/ads/news-and-inspiration/ads-leaderboard/youtube-ads-leaderboard-2021-cannes-edition/>.

References

- [1] K. Swani and L. I. Labrecque, "Like, comment, or share? Self-presentation vs. brand relationships as drivers of social media engagement choices," *Marketing Letters*, vol. 31, no. 2-3, pp. 279–298, 2020.
- [2] D. Mladenović, K. Koštiál, N. Ljepava, O. Částek, and Y. Chawla, "Emojis to conversion on social media," *International Journal of Consumer Studies*, vol. 47, no. 3, pp. 977–994, 2023.
- [3] X. Wang, M. Cheng, S. Li, and R. Jiang, "The interaction effect of emoji and social media content on consumer engagement: a mixed approach on peer-to-peer accommodation brands," *Tourism Management*, vol. 96, Article ID 104696, 2023.
- [4] R. Dolan, J. Conduit, C. Frethey-Bentham, J. Fahy, and S. Goodman, "Social media engagement behavior: a framework for engaging customers through social media content," *European Journal of Marketing*, vol. 53, no. 10, pp. 2213–2243, 2019.
- [5] S. S. Gaur, H. Herjanto, and M. Makkar, "Review of emotions research in marketing, 2002–2013," *Journal of Retailing and Consumer Services*, vol. 21, no. 6, pp. 917–923, 2014.
- [6] J. Berger and K. L. Milkman, "Emotion and virality: what makes online content go viral?," *NIM Marketing Intelligence Review*, vol. 5, no. 1, pp. 18–23, 2013.
- [7] L. D. Hollebeek, M. S. Glynn, and R. J. Brodie, "Consumer brand engagement in social media: conceptualization, scale development and validation," *Journal of Interactive Marketing*, vol. 28, no. 2, pp. 149–165, 2014.
- [8] W. W. Moe and D. A. Schweidel, "Online product opinions: incidence, evaluation, and evolution," *Marketing Science*, vol. 31, no. 3, pp. 372–386, 2012.
- [9] L. McShane, E. Pancer, M. Poole, and Q. Deng, "Emoji, playfulness, and brand engagement on Twitter," *Journal of Interactive Marketing*, vol. 53, no. 1, pp. 96–110, 2021.
- [10] L. Dessart, "Social media engagement: a model of antecedents and relational outcomes," *Journal of Marketing Management*, vol. 33, no. 5-6, pp. 1–25, 2017.
- [11] X. Wang and Z. Liu, "Online engagement in social media: a cross-cultural comparison," *Computers in Human Behavior*, vol. 97, pp. 137–150, 2019.
- [12] D. He, S. Melumad, and M. T. Pham, "The pleasure of assessing and expressing our likes and dislikes," *Journal of Consumer Research*, vol. 46, no. 3, pp. 545–563, 2019.
- [13] L. J. Kornish and S. M. Jones, "Raw ideas in the fuzzy front end: verbosity increases perceived creativity," *Marketing Science*, vol. 40, no. 6, pp. 1106–1122, 2021.
- [14] B. Haven, *Marketing's New Key Metric: Engagement*, Marketing, 2007.
- [15] L. Hollebeek, "Exploring customer brand engagement: definition and themes," *Journal of Strategic Marketing*, vol. 19, no. 7, pp. 555–573, 2011.
- [16] L. I. Labrecque, K. Swani, and A. T. Stephen, "The impact of pronoun choices on consumer engagement actions: exploring top global brands' social media communications," *Psychology & Marketing*, vol. 37, no. 6, pp. 796–814, 2020.
- [17] R. P. Bagozzi, M. Gopinath, and P. U. Nyer, "The role of emotions in marketing," *Journal of the Academy of Marketing Science*, vol. 27, no. 2, pp. 184–206, 1999.
- [18] L. Watson and M. T. Spence, "Causes and consequences of emotions on consumer behaviour: a review and integrative cognitive appraisal theory," *European Journal of Marketing*, vol. 41, no. 5/6, pp. 487–511, 2007.
- [19] S. P. Brown, W. L. Cron, and J. W. Slocum Jr., "Effects of goal-directed emotions on salesperson volitions, behavior, and performance: a longitudinal study," *Journal of Marketing*, vol. 61, no. 1, pp. 39–50, 1997.
- [20] J. Bloemer and K. De Ruyter, "Customer loyalty in high and low involvement service settings: the moderating impact of positive emotions," *Journal of Marketing Management*, vol. 15, no. 4, pp. 315–330, 1999.
- [21] C. J. White, "The impact of emotions on service quality, satisfaction, and positive word-of-mouth intentions over time," *Journal of Marketing Management*, vol. 26, no. 5-6, pp. 381–394, 2010.
- [22] J. Guerreiro, P. Rita, and D. Trigueiros, "Attention, emotions and cause-related marketing effectiveness," *European Journal of Marketing*, vol. 49, no. 11/12, pp. 1728–1750, 2015.
- [23] G. Walsh, E. Shiu, L. M. Hassan, N. Michaelidou, and S. E. Beatty, "Emotions, store-environmental cues, store-choice criteria, and marketing outcomes," *Journal of Business Research*, vol. 64, no. 7, pp. 737–744, 2011.
- [24] R. W. Mizerski and J. D. White, "Understanding and using emotions in advertising," *Journal of Consumer Marketing*, vol. 3, no. 4, pp. 57–69, 1986.
- [25] H. Zhang, J. Sun, F. Liu, and J. G. Knight, "Be rational or be emotional: advertising appeals, service types and consumer responses," *European Journal of Marketing*, vol. 48, no. 11/12, pp. 2105–2126, 2014.
- [26] O. F. Koch and A. Benlian, "Promotional tactics for online viral marketing campaigns: how scarcity and personalization affect seed stage referrals," *Journal of Interactive Marketing*, vol. 32, no. 1, pp. 37–52, 2015.
- [27] P. Mukherjee, S. Dutta, and A. De Bruyn, "Did clickbait crack the code on virality?," *Journal of the Academy of Marketing Science*, vol. 50, no. 3, pp. 482–502, 2022.
- [28] C. E. Tucker, "The reach and persuasiveness of viral video ads," *Marketing Science*, vol. 34, no. 2, pp. 281–296, 2015.
- [29] K. Libert and K. Tynski, "The emotions that make marketing campaigns go viral," *Harvard Business Review*, vol. 1, no. 1, Article ID 108230, 2013.

- [30] E. Akpınar and J. Berger, “Valuable virality,” *Journal of Marketing Research*, vol. 54, no. 2, pp. 318–330, 2017.
- [31] A. Borah, S. Banerjee, Y. T. Lin, A. Jain, and A. B. Eisingerich, “Improvised marketing interventions in social media,” *Journal of Marketing*, vol. 84, no. 2, pp. 69–91, 2020.
- [32] H. T. Nguyen and M. Chaudhuri, “Making new products go viral and succeed,” *International Journal of Research in Marketing*, vol. 36, no. 1, pp. 39–62, 2019.
- [33] G. J. Tellis, D. J. MacInnis, S. Tirunillai, and Y. Zhang, “What drives virality (sharing) of online digital content? The critical role of information, emotion, and brand prominence,” *Journal of Marketing*, vol. 83, no. 4, pp. 1–20, 2019.
- [34] R. Rietveld, W. Van Dolen, M. Mazloom, and M. Worrying, “What you feel, is what you like influence of message appeals on customer engagement on Instagram,” *Journal of Interactive Marketing*, vol. 49, no. 1, pp. 20–53, 2020.
- [35] C. Schulze, L. Schöler, and B. Skiera, “Not all fun and games: viral marketing for utilitarian products,” *Journal of Marketing*, vol. 78, no. 1, pp. 1–19, 2014.
- [36] J. Ge and U. Gretzel, “Emoji rhetoric: a social media influencer perspective,” *Journal of Marketing Management*, vol. 34, no. 15–16, pp. 1272–1295, 2018.
- [37] E. Aioisa, “The anatomy of an effective e-mail subject line: how to stand out in a crowded inbox,” *Journal of Digital & Social Media Marketing*, vol. 8, no. 3, pp. 244–250, 2020.
- [38] C. H. Leung and W. T. Y. Chan, “Using emoji effectively in marketing: an empirical study,” *Journal of Digital & Social Media Marketing*, vol. 5, no. 1, pp. 76–95, 2017.
- [39] L. Boman, G. U. Hewage, and J. Hasford, “The effect of emoji incongruency in social media: an abstract,” in *Marketing Opportunities and Challenges in a Changing Global Marketplace. AMSAC 2019. Developments in Marketing Science: Proceedings of the Academy of Marketing Science*, S. Wu, F. Pantoja, and N. Krey, Eds., Springer, Cham, 2020.
- [40] R. G. Indwar and A. S. Mishra, “Emojis: can it reduce post-purchase dissonance?,” *Journal of Strategic Marketing*, vol. 31, no. 4, pp. 918–939, 2023.
- [41] X. Huang, M. S. Kader, and S. Kim, “Let’s play with emojis! How to make emojis more effective in social media advertising using promocodes and temporal orientation,” *Journal of Research in Interactive Marketing*, vol. 16, no. 4, pp. 665–682, 2022.
- [42] S. Zhang, M. D. de Jong, and J. F. Gosselt, “Microblogging for engagement: effects of prior company involvement, communication strategy, and emojis on Western and Chinese users,” *Journal of International Consumer Marketing*, vol. 34, no. 5, pp. 616–630, 2022.
- [43] Y. Li and Y. Xie, “Is a picture worth a thousand words? An empirical study of image content and social media engagement,” *Journal of Marketing Research*, vol. 57, no. 1, pp. 1–19, 2020.
- [44] G. S. Urumutta Hewage, Y. Liu, Z. Wang, and H. Mao, “Consumer responses toward symmetric versus asymmetric facial expression emojis,” *Marketing Letters*, vol. 32, no. 2, pp. 219–230, 2021.
- [45] L. W. Smith and R. L. Rose, “Service with a smiley face: emotional contagion in digitally mediated relationships,” *International Journal of Research in Marketing*, vol. 37, no. 2, pp. 301–319, 2020.
- [46] D. A. Aaker, *Managing Brand Equity: Capitalizing on the Value of a Brand Name*, Simon and Schuster, 2009.
- [47] A. Sela and J. Berger, “How attribute quantity influences option choice,” *Journal of Marketing Research*, vol. 49, no. 6, pp. 942–953, 2012.
- [48] R. E. Petty and J. T. Cacioppo, “The effects of involvement on responses to argument quantity and quality: central and peripheral routes to persuasion,” *Journal of Personality and Social Psychology*, vol. 46, no. 1, pp. 69–81, 1984.
- [49] N. H. Lurie, “Decision making in information-rich environments: the role of information structure,” *Journal of Consumer Research*, vol. 30, no. 4, pp. 473–486, 2004.
- [50] S. M. Broniarczyk and J. G. Griffin, “Decision difficulty in the age of consumer empowerment,” *Journal of Consumer Psychology*, vol. 24, no. 4, pp. 608–625, 2014.
- [51] R. Mugge and D. W. Dahl, “Seeking the ideal level of design newness: consumer response to radical and incremental product design,” *Journal of Product Innovation Management*, vol. 30, no. S1, pp. 34–47, 2013.
- [52] S. Hoeffler, “Measuring preferences for really new products,” *Journal of Marketing Research*, vol. 40, no. 4, pp. 406–420, 2003.
- [53] A. J. Mills and J. John, “Brand stories: bringing narrative theory to brand management,” *Journal of Strategic Marketing*, vol. 28, pp. 1–19, 2020.
- [54] A. G. Woodside, S. Sood, and K. E. Miller, “When consumers and brands talk: storytelling theory and research in psychology and marketing,” *Psychology & Marketing*, vol. 25, no. 2, pp. 97–145, 2008.
- [55] Y. Chang, Y. Li, J. Yan, and V. Kumar, “Getting more likes: the impact of narrative person and brand image on customer-brand interactions,” *Journal of the Academy of Marketing Science*, vol. 47, no. 6, pp. 1027–1045, 2019.
- [56] K. A. Quesenberry and M. K. Coolsen, “Drama goes viral: effects of story development on shares and views of online advertising videos,” *Journal of Interactive Marketing*, vol. 48, no. 1, pp. 1–16, 2019.
- [57] E. Simakova and D. Neyland, “Marketing mobile futures: assembling constituencies and creating compelling stories for an emerging technology,” *Marketing Theory*, vol. 8, no. 1, pp. 91–116, 2008.
- [58] M. Jockers, *Introduction to the Syuzhet Package*, The Comprehensive R Archive Network, 2017.
- [59] A. Maydeu-Olivares and C. Garcia-Forero, “Goodness-of-fit testing,” *International Encyclopedia of Education*, vol. 7, no. 1, pp. 190–196, 2010.
- [60] J. M. Wooldridge, *Introductory Econometrics: A Modern Approach*, Cengage Learning, 2015.
- [61] L. J. Suchower and M. D. Copenhaver, “Using logistic regression to test for interaction in the presence of zero cells,” in *10th Annual Northeast SAS Users Group Conference*, pp. 5–7, Baltimore, Maryland, 1997.
- [62] J. H. Stock and M. W. Watson, *Introduction to Econometrics, Updated 3rd ed*, Pearson, Essex, 2015.
- [63] K. L. Milkman and J. Berger, “What makes online content viral?,” *Journal of Marketing Research*, vol. 49, no. 2, pp. 192–205, 2012.
- [64] E. E. Ko, D. Kim, and G. Kim, “Influence of emojis on user engagement in brand-related user generated content,” *Computers in Human Behavior*, vol. 136, Article ID 107387, 2022.