Proceedings of the 5th International Conference on Literature, Language, and Culture Development
DOI: 10.54254/2753-7064/2026.32362

Dynamic Sentiment Patterns in Social Media Crisis Communication: A Comparative Study of Starbucks and Tesla

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Abstract. Nowadays, with the popularity of social media, information shifted from the previous crisis dissemination method to a more complex and rapid online spread. Public sentiment had a greater impact on shaping corporate reputation and market results. This study examines how social media emotions spread on the Internet and influence public perception during corporate crises and conducts a comparative analysis using two different cases. Due to data access restrictions, this article presents an analysis of manually collected tweet samples: 52 tweets from Starbucks' 2024 union movement and 30 tweets from Tesla's November 2023 vehicle recall. Manually mark the emotions as positive, neutral or negative based on the attitude expressed in the tweet to the company and events. The survey results reveal significant differences: Starbucks' tweets are mainly positive (56%), with strong public support for its workers, while Tesla's discourse on product safety issues is polarized (37% positive, 40% negative). These patterns indicate that labor disputes generate more persistent sympathy, while discussions triggered by product safety crises are more objective and balanced. This research contributes to crisis communication literature by emphasizing the importance of conducting specific analyses based on different types of crises and provides practical significance for enterprises' crisis response strategies and investors' decision-making. The limitations of this paper include a small sample size and the lack of quantitative analysis, which points out the direction for future research on larger datasets.

Keywords: Dynamic sentiment patterns, social media crisis, Starbucks, Tesla

1. Introduction

Social media has greatly transformed the way corporate crises break out and spread. It was unimaginable 20 years ago that a post could be shared by a million people within an hour. Shape public perception and influence the judgment of stakeholders with more unpredictable trends. From labor disputes to product safety issues, the current crisis has evolved into a complex online phenomenon. In these complex network structures, public sentiment is rapidly ignited and continuously magnified.

To deal with the current situation, practitioners need to rapidly understand how social media sentiment changes in different types of corporate crises. However, most of the existing research relies on large-scale automated data collection and studies relatively simple types of crises. There is not much attention paid to comparing different types of crises such as labor disputes and product

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safety incidents, it is impossible to fully grasp all different patterns of public response. Furthermore, the practical challenges of data access have posed obstacles for many potential researchers such as students and independent scholars when conducting empirical studies.

To fill the research gap mentioned above, this study conducted a comparative analysis of two representative types of corporate crises by using manually collected social media data. This study selects "Starbucks' 2024 unionization Movement" to represent labor disputes and "Tesla's November 2023 vehicle recall incident" to represent product safety crises. Due to the limitations of Twitter API access, the samples in this article were manually collected and annotated: 52 tweets for the Starbucks case and 30 tweets for the Tesla case. To conduct a deep analysis of the distribution characteristics of public emotions, based on the attitudes expressed to relevant companies and events in tweets, emotions are classified into positive, neutral and negative, therefore conducting a qualitative analysis of emotional patterns and discussion topics.

This study contributes to the literature on crisis communication by demonstrating the significance of setting specific analytical frameworks based on different types of crises. It also offers practical insights into specific types: for labor disputes of consumer-centered companies, emotional engagement and long-term brand restoration strategies are more efficient. When technology companies discover product safety issues, they should demonstrate technical transparency and communicate promptly for remediation. Targeted strategies for different types of crises were presented to investors. The limitations of this study are mainly reflected in the limited sample size and the lack of quantitative analysis. Future research should focus on whether to adopt larger-scale datasets and automated collection methods.

2. Literature review

2.1. The brand crisis management theory

Social media has changed the logic of traditional crisis management. In the past, enterprises usually controlled the dissemination of information through press conferences and official statements. Therefore, enterprises have ample time to discuss, formulate and improve their response strategies.

Today, the path of information dissemination is no longer linear but presents a network structure. Emotion becomes the core driving force of communication, and users at each information node have the chance to become a communication node.

Samet's 2024 study shows that 41% of a company's brand value comes from its online reputation [1]. Similarly, research indicates that the social media crisis has significantly shortened the golden time for enterprises to respond to crises, which may lead to a shrinkage in market value.

2.2. Applications for sentiment analysis in business

Emotion analysis technology has undergone three major upgrades. Early methods relied on thesaurus and contextual understanding abilities with limited accuracy. Although the introduction of machine learning methods significantly improved classification performance, the real turning point was the introduction of pre-trained models such as BERT and RoBERTa, which fundamentally changed this field. Liu and his team proposed the RoBERTa model in 2019, performing particularly well in classifying the sentiment of financial texts [2]. Shu's research further indicates that by fine-tuning RoBERTa in specific fields, its accuracy in identifying satirical comments can be significantly enhanced [3].

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The achievements brought about by the technological advances are reflected in the practice of quantitative investment. According to Todd's 2025 research, investment institutions that use multimodal sentiment analysis can achieve higher strategic returns [4]. The core effects of these systems could detect changes in market sentiment in advance and create crucial time for trading decisions.

2.3. Empirical study on market reactions

Among numerous studies, the one conducted by Bartov et al. in 2018, which revealed the correlation between social media sentiment and stock prices, is highly representative. Through discussions on the components of the S&P 500 index on Twitter, this experiment confirmed a significant negative correlation between negative sentiment and subsequent stock returns [5]. High levels of negative sentiment are usually accompanied by a decline in stock prices [5]. This correlation is particularly evident in technology stocks [5].

The event study method provides precise measurement tools. Cunningham's case analysis in his book published in 2021 shows that the event study method can accurately separate the net impact of social media crises on company stock prices and eliminate the interference of other factors [6].

From a technical perspective, the neural network architecture established by Mollah et al. in 2023 enables real-time monitoring of emotional changes on social media. This system is characterized by low latency and real-time monitoring. It provides strong technical support for strategy formulation.

2.4. Research gap summary

The deficiencies of the existing research are reflected in three aspects. Crisis communication is a dynamic process. However, most related studies employ a static analysis framework and only examine the distribution of emotions at specific time points. The factor of network structure has not been given sufficient attention either. Most models adopt the homogenization assumption, ignoring the structural differences in individual influence and key opinion leaders. The research by Cartea et al. on automated market makers confirmed that the impact of network topology on the efficiency of information dissemination cannot be ignored [7]. Tzimiris et al. found that different language models performed differently when dealing with the same sentiment analysis task [8]. Therefore, the different user behaviors, content structures and interaction mechanisms on social media platforms are very likely to lead to different emotional dissemination patterns. The most crucial issue is the lack of dynamic modeling. How emotions flow in real time on the network, how they fade over time, and how they spread between different nodes. These deficiencies have restricted the predictive ability and practical value of the research. This study will explore through three dimensions: tracking the evolution process of emotions through dynamic modeling, analyzing how network structure affects communication efficiency, and establishing a cross-platform comparison framework. Lay the foundation for establishing a practical early warning system.

3. Research methodology

This chapter presents the overall design framework of this study. The standardized process of data processing, the criteria for case selection, the sentiment analysis architecture based on bert-base-uncase, and the network analysis method used to examine the information dissemination pattern during enterprise crises will be elaborated.

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3.1. Research framework design

For data processing, this study follows the following procedures: cleaning the original social media content, removing advertisements, filtering irrelevant discussions, and deleting duplicate posts. Normalize the emotion score to the interval [0,1] for comparability. At the same time, adjust the price data based on dividend and stock split factors. Identify and remove outliers based on the 3σ principle to ensure the robustness of data analysis.

This research includes four stages, covering data collection, sentiment modeling, network dissemination analysis and market effect testing. The objective of this framework is to track the dynamic dissemination path of complete information from social media to the financial market.

This study takes the Starbucks' public relations crisis in 2024 and the recall of Tesla in 2023 as the analysis objects. They respectively represent the brand crisis in the consumer goods industry and the product safety crisis in the technology industry. The selection of cases follows three criteria: the event has a significant influence, is adequately discussed on social media, and the relevant stock price data is complete and available. By comparing different industries, revealing the structural differences in the dissemination patterns of various types of crises.

3.2. Model construction

In this study, sentiment analysis adopted Bert-base-uncase architecture as the basic model, which demonstrated strong performance in the task of social media text classification. The model design further incorporates the fine-tuning strategy for dealing with satire proposed by Shu [3].

The construction of the communication network follows the standard social network analysis methods. Specifically, it is manifested as taking users as nodes, with edges representing forwarding and mentioning relationships, to construct a dynamic dissemination network. Network metrics cover four dimensions: clustering coefficient (reflecting the degree of community aggregation), node centrality (identifying key opinion leaders), dissemination depth (measuring the scope of information dissemination), and the aggregation effect of users with similar emotions. According to the established methods of social network analysis, these indicators constitute the framework of the structural characteristics of information dissemination [9]. The computational framework draws on the relevant achievements of dynamic network topology analysis methods [10].

Due to practical constraints such as data acquisition, this study failed to conduct an analysis of methods like Granger causality test and event study. The framework of the relevant analysis discussed here is to provide methodological groundwork for subsequent research. The research, in combination with Cunningham's causal reasoning framework, isolates the "pure effect" of social media crises from other market factors, reducing the interference of other factors [6].

4. Data analysis and results

The empirical analysis in this chapter is based on manually collected tweet samples. Taking the cases of Starbucks and Tesla as the research objects, focusing on the expression patterns of public sentiment and making a comparison of the two different types of crises.

4.1. Descriptive statistics

Due to data access limitations, this study uses manually collected tweet samples. This study collected 52 related tweets for the Starbucks union movement case that began in March 2024. For the case of Tesla vehicle recall, this study collected 30 related tweets from November 2023.

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Emotions are manually marked. The attitude towards the case company and the event is marked as positive, neutral or negative based on the content of the tweet.

Distribution statistics show that in the Starbucks sample, positive emotions account for 56% of the tweets, neutral emotions for 29%, and negative emotions for 15%. The dominance of positive emotions reflects the widespread public support for Starbucks employees during the unionization movement. Users called for a boycott and shared the news that a union was established in the new store, put pressure on the company by showing their support for the striking workers.

In Tesla's sample, positive emotions accounted for 37% of tweets, neutral emotions for 23%, and negative emotions for 40%. Compared with Starbucks, the higher proportion of negative emotions indicates that product safety issues are often more likely to trigger public critical reactions than labor disputes. More positive tweets defended Tesla and highlighted the unique advantage of wireless updates in addressing recall issues.

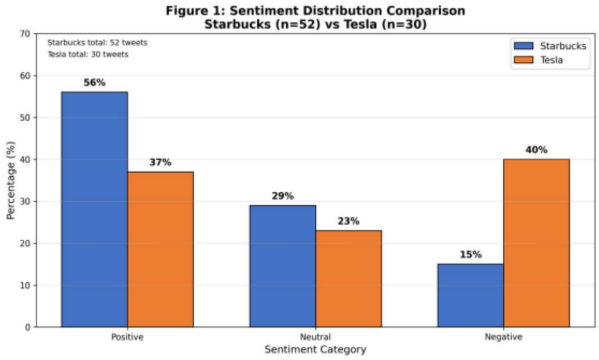

Figure 1. Sentiment distribution comparison Starbucks (n=52) vs Tesla (n=30)

Figure 1 visually summarizes the emotional composition of these two situations. As shown in the figure, Starbucks' positive emotions dominate (56%) in the discussions. Tesla's positive and negative viewpoints account for 37% and 40% respectively, showing a clear polarization feature.

4.2. Sentiment dynamics analysis

Based on manually labeled tweet samples, this chapter further observes the dynamic characteristics of emotional evolution in two scenarios.

In the Starbucks sample, tweets that began in March 2024 demonstrated strong and sustained support for union workers. Positive emotions remained dominant throughout the collection period, news of the establishment of a union in the new store kept spreading, and discussions on workers' rights had a broader impact. The tone is usually celebratory and encouraging. Negative emotions are rather marginal. Users mainly question the motivations of the trade union or respond indifferently to the incident.

The emotional evolution of the Tesla sample is more extreme. After the recall was announced in November 2023, negative emotions rapidly took over. Users expressed concerns about safety, frustration with frequent recalls, and doubts about Tesla's quality control. However, the positive sentiment is also considerable. Users' defenses emphasize the ability of wireless update technology to address the recall. Neutral tweets focused on discussing the technical details of the recall and cross-brand comparisons.

The above observations reveal the emotional differences between the two cases. The controversy over Starbucks has sparked a continuous accumulation of positive emotions towards its workers.

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Tesla's recall has triggered even more polarized reactions. The point of the dispute lies in the significance of the recall and the effectiveness of Tesla in resolving the issue.

4.3. Cross-case comparison

The comparison between Tesla and Starbucks reveals several differences in specific industries.

Table 1. Rules to format sections

Dimension	Starbucks	Tesla
Dominant Sentiment	Positive	Polarized
Positive %	56%	37%
Neutral %	29%	23%
Negative %	15%	40%
Discussion Focus	Workers' rights, solidarity	Safety, OTA updates, recalls
Defense Mechanism	None (support workers)	OTA update advantage
Recover Factors	Emotional, CSR	Technical transparency

As shown in Table 1, 56% of the Starbucks samples were positive words, while negative emotions only accounted for 15%. This implies that the labor solidarity movement has greater potential to inspire widespread public sympathy. The proportion of positive sentiment (37%) and negative sentiment (40%) in the Tesla sample is similar, indicating that product safety issues have polarized public opinion.

There are also significant differences in the distribution of topics. Starbucks' discussions mostly focused on workers' rights, fair wages, union unity and corporate responsibility. Tesla's discussions focused more on vehicle safety, the nature of wireless updates, and comparisons with traditional recalls.

Supporters of Tesla have repeatedly emphasized that many recalls can be addressed through software updates rather than physical repairs. This argument is used to weaken the severity of the recall. Similar defense mechanism was not mentioned in the discussions at Starbucks.

Based on comprehensive qualitative observation, the emotional recovery path of the Tesla case is more dependent on technical arguments, while the emotions of the Starbucks case are more closely related to emotions such as social responsibility. The differences in discussion content and emotional patterns indicate that the analytical framework developed for a single crisis type cannot be directly transferred to another crisis. This conclusion provides a strong argument for offering specific analytical methods for particular industries.

4.4. Implications

For consumer goods enterprises (such as Starbucks), crisis response strategies should focus on emotional investment and long-term brand restoration. The strong public support for workers indicates that stakeholders' expectations of enterprises extend beyond mere economic performance to the fulfillment of social responsibilities and substantive commitments. For technological enterprises (such as Tesla), in response to crises, priority should be given to rapid communication and technological transparency. Maintaining transparency of physical defects while emphasizing the unique advantages of wireless updates can help guide public perception towards a positive direction. For investors, the above-mentioned industry differences imply different trading strategies.

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Technology stocks are more suitable for short-term reversal strategies because sentiment is often driven by events. The longer the value investment cycle of consumer goods stocks is, the more it aligns with the investment logic. For researchers, these findings emphasize the importance of specific models for crisis types. General sentiment analysis tools that are divorced from domain knowledge may miss key contextual clues and weaken the power of explanation and prediction.

5. Conclusion

This article takes the trade union movement of Starbucks in 2024, and the vehicle recall incident of Tesla in 2023 as the research objects to explore the social media emotional characteristics of two different types of enterprises in crisis situations. An analysis based on manually collected tweets (52 for Starbucks and 30 for Tesla) has revealed clear industry-specific patterns. Starbucks discussions were dominated by positive emotions (56%), reflecting the public's broad support for workers' rights. Discussions related to Tesla are polarized (37% positive and 40% negative), with the debate focusing on safety issues and the advantages of wireless update technology. The above differences indicate that labor dispute crises are more likely to stimulate sustained sympathetic participation, while product safety crises tend to trigger balanced technical debates.

This study has several limitations. Due to the access restrictions of the Twitter API, the sample size is relatively small and may not fully represent the broader public discussion. Emotion analysis is done manually, which inevitably introduces potential subjectivity. The constraints of sample size and Twitter metadata acquisition have led to the inability to implement quantitative analyses such as Granger causality tests and network structure analysis. The collection process of Twitter may involve selection bias. In the case of Tesla, the dual semantics of "recall" need to be carefully filtered. Given these limitations, the research results should be regarded as the fruits of exploration. Future research will need to rely on larger datasets and automatic collection methods to systematically verify these observations.

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