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A MACHINE LEARNING APPROACH TO EXPLORING SENTIMENTS OF USER DURING AN IT OUTAGE: THE CROWDSTRIKE CASE

*Dilek GÖNÇER DEMİRAL**

Abstract

Today, social media platforms are the fastest, most interactive public arenas, capturing the pulse of global crises and instantly shaping public sentiments. These dynamic structures multiply the speed of information spread, allowing the simultaneous interactions of millions of users to reveal different dimensions of an event. This study examined the effects of the Crowdstrike incident on July 19, 2024, a major IT outage affecting daily life, on social media platforms through sentiment analysis. A total of 1536 tweets were analysed using the Orange data mining and machine learning software. The analysis reveals that the public's reaction was multi-dimensional, with a dominant neutral sentiment. However, detailed emotion analyses based on Ekman and Plutchik algorithms showed various coexisting emotions, including joy, surprise, sadness, trust, and fear, proving emotional complexity is intertwined with information sharing and humour during a crisis. Furthermore, topic modeling analysis suggests that such a technical incident can quickly link to seemingly unrelated political agendas, highlighting social media's power to shift an event from a technical to a social and political context. These findings suggest that public response to IT crises is not merely technical but inherently social, emotional, and political in nature, underscoring the need for crisis communication strategies that account for emotional complexity and discourse dynamics on social media. This study contributes to the literature by addressing a gap in the literature through a multi-method sentiment analysis of a global IT outage, integrating VADER, Ekman, and Plutchik emotion models alongside topic modeling, and provides a replicable framework for analysing public reactions to technology-driven crises.

Keywords: *Sentiment analysis, Machine learning, Social media, Crowdstrike.*

Bir BT Kesintisi Sırasında Kullanıcı Duygularının İncelenmesi: CrowdStrike Vakası için Bir Makine Öğrenmesi Yaklaşımı

Öz

Günümüzde sosyal medya platformları, küresel krizlerin nabzını tutan ve kamuoyunun duygularını anında şekillendiren, en hızlı ve en etkileşimli kamusal alanlar haline gelmiştir. Bu dinamik yapılar, bilginin yayılma hızını artırarak milyonlarca kullanıcının eş zamanlı etkileşimleri aracılığıyla bir olayın farklı boyutlarının ortaya çıkmasını sağlamaktadır. Bu çalışma, 19 Temmuz 2024 tarihinde günlük yaşamı etkileyen büyük bir BT kesintisine yol açan CrowdStrike olayının sosyal medya platformlarındaki yansımalarını duygu analizi yoluyla incelemektedir. Toplam 1.536 tweet, Orange veri madenciliği ve makine öğrenmesi yazılımı kullanılarak analiz edilmiştir. Analiz sonuçları, kamuoyu tepkilerinin çok boyutlu bir yapıya sahip olduğunu ve nötr duygu durumunun baskın olduğunu göstermektedir. Bununla birlikte, Ekman ve Plutchik algoritmalarına dayalı ayrıntılı duygu analizleri; sevinç, şaşkınlık, üzüntü, güven ve korku gibi bir arada var olan çeşitli duyguları ortaya koyarak, kriz dönemlerinde duygusal karmaşıklığın bilgi paylaşımı ve mizah ile iç içe geçtiğini göstermektedir. Ayrıca konu modellemesi (topic modelling) analizi, bu tür teknik bir olayın kısa sürede, görünürde ilgisiz siyasi gündemlerle ilişkilendirilebildiğini ortaya koymakta ve sosyal medyanın bir olayı teknik bağlamdan sosyal ve politik bir bağlama taşıma gücünü vurgulamaktadır. Bu bulgular, BT krizlerine yönelik kamusal tepkinin yalnızca teknik değil; aynı zamanda doğası gereği sosyal, duygusal ve politik olduğunu göstermektedir. Bu nedenle, kriz iletişimi stratejilerinin sosyal medyadaki duygusal karmaşıklığı ve söylem dinamiklerini dikkate alacak şekilde geliştirilmesi gerekmektedir. Bu çalışma, küresel bir BT kesintisini çok yöntemli duygu analizi yaklaşımıyla ele alarak literatürdeki bir boşluğu doldurmakta; VADER, Ekman ve Plutchik duygu modellerini konu modelleme ile birlikte kullanmakta ve teknoloji kaynaklı krizlere yönelik kamusal tepkilerin analiz edilmesi için tekrarlanabilir bir çerçeve sunmaktadır.

Anahtar Kelimeler: *Duygu analizi, Makine öğrenmesi, Sosyal medya, Crowdstrike.*

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1. Introduction

Today, social media have turned into the most important platforms for the rapid spread of information and high-powered interaction and have also evolved into an environment that allows people to express their emotions and write down their immediate feelings. While it has become a place where people can freely express their opinions, it has also become a valuable data center for businesses. Through these platforms, businesses gain the opportunity to develop and improve themselves by receiving feedback on their products and services. Therefore, social networks have become digital hubs where valuable and implicit information can be obtained through accurate analysis.

Social media applications are generally technologies through which users convey all kinds of media content over internet-based platforms (Gabriel & Röhrs, 2017). Social media serves as a rich data source where millions of content pieces are uploaded and people's views can be expressed daily, making them one of the best areas for marketing and influencing people today. It attracts great attention both in terms of promoting products and services and measuring public perception (Gönçer-Demiral, 2024). Digital social networks such as Facebook, X (Formerly Twitter), YouTube, and WhatsApp are also used as a means of socialization in society. X, in particular, stands out as a platform with a large-scale interaction and communication network that facilitates instant online communication. In this context, X's impact on social movements and its potential for analysis are attracting significant interest (Zarrabeitia-Bilbao et al., 2022). Tweets not only reveal individuals' thoughts on a given topic but also express their emotions through text or emojis. Analysing emotions provides a quick and efficient way to gain insights into a particular subject. Individuals' emotions about a topic can be measured through sentiment analysis

Sentiment analysis, also known as opinion mining, is a computer science study that aims to understand public impressions of a specific subject by examining people's viewpoints and emotions regarding that subject (Mir & Sevukan, 2024). It is an analytical method rooted in text classification, which involves processing language, linguistic structures, and data derived from text mining. This process aims to analyse an author's opinions, sentiments, and emotions concerning a specific topic (Mailoa, 2021). Sentiment analysis is a natural language processing (NLP) method used to interpret emotions in texts, which can be considered unstructured data. The texts written by individuals are taken as input, and the underlying emotions within these texts are categorized as positive, negative, or neutral (Kameswari et al., 2019). Sentiment analysis, which includes lexicon-based applications and statistical (machine learning) methods, is crucial for quickly interpreting critical data, especially during times of crisis. Historically, the world has witnessed crises on a global scale, such as wars, economic downturns, diseases, accidents, and technological disruptions. In these periods, social networks play an incredible role and exert strong influence. The global technology-based crisis caused by CrowdStrike in 2024 also witnessed the impact of social networks.

CrowdStrike is a cloud-based American technology company operating in the field of cybersecurity, utilizing advanced technologies such as artificial intelligence, machine learning, and behavioral analytics in its Falcon platform to detect and mitigate threats (Banerjee, 2024). CrowdStrike protects companies against a wide range of threats, including identity-based threats, malware, and cyber espionage. Its services are used by government agencies, companies listed in the Fortune 500, and international organizations (Camacho, 2024).

On July 19, 2024, the Falcon sensor update released by CrowdStrike caused unexpected system crashes and "Blue Screen of Death" (BSOD) errors on millions of computers running the Windows operating system. This faulty update affected an estimated 8.5 million Microsoft Windows systems, causing a widespread global service outage. The outage also affected the Microsoft Azure platform, disrupting services in many critical areas, including aviation, banking, healthcare, finance, tourism, and emergency services. Globally, the incident caused numerous flight cancellations, interruptions in critical patient care, and preventing financial institutions from being able to serve their customers. Although this was not a direct cyberattack, it triggered a significant operational turmoil reminiscent of major cyber incidents in the past. Estimates of the financial impact of the incident are approximately $4 billion to $6 billion worldwide (George, 2024). Delta Airlines claimed it lost $380 million and was forced to pay $170 million in costs due to the massive flight cancellations caused by the CrowdStrike outage (Independent, 2024).

Such a widespread outage and service disruptions have sparked intense debate on social media, quickly becoming a trending topic, especially on X, one of the platforms where instant sharing is most frequent. The incident quickly generated a global impact through hashtags and viral sharing. This demonstrates the interactivity and power of social networks during a specific crisis. It is undeniable that social networks not only facilitate the flow of information during such a critical time, but also contribute to the rapid spread of misinformation, the creation of manipulative content, and the shaping of public perception in general. In this context, social networks provide an ideal ground for revealing the emotional reactions and perceptions generated within the public sphere.

The aim of this study is to analyse tweets collected with the #Crowdstrike hashtag on the X platform between July 19-26, 2024. During this period, a dataset consisting of 1,536 tweets was generated, and sentiment analysis was conducted on these data. For data analysis, Orange software, which incorporates various machine learning and data mining algorithms, was used. The methodology applied in this study provides a systematic approach for the quantitative and qualitative analysis of social network data. Within this approach, data was first collected from X, followed by preprocessing step to clean noisy data and ensure data consistency. Subsequently, a word cloud was used to reveal the frequency and significance of the keywords in the dataset. While sentiment analysis determined the general public attitude toward the incident, tweet profiling enabled the classification of emotions, and topic modelling uncovered the hidden themes and discussion topics within the tweets. In this way, the scientific analysis of unstructured social network data aims to provide a deeper understanding of public reactions and the dynamics of the crisis. This study yielded valuable insights into a wide range of emotions by applying sentiment analysis techniques to tweets related to the Crowdstrike hashtag.

While numerous studies in the literature focus on sentiment analysis conducted on platform X, research examining sentiment analysis in the context of a technical disruption that rapidly escalated into a multi-dimensional global crisis remains limited. The studies that most directly examined the CrowdStrike event (Banerjee, 2024; George, 2024; Mugu et al., 2024; Sayonara & Deemantha, 2024) approached it from technical, institutional, and economic perspectives; largely focusing on the emotional and expressive dimensions of the public's real-time social media response. However, neither these studies nor the broader literature directly addresses the emotional and discursive dimensions of the real-time emergence of an infrastructure-based IT outage on social media. In this context, the present study offers a unique contribution by treating the CrowdStrike-related IT outage not merely as a technical failure, but as a global event with social, emotional, and discursive impacts. The simultaneous impact of a short-term system disruption on different sectors and geographic regions highlights the diversity and transformation of emotional responses expressed by individuals on social media. Accordingly, this study contributes to a better understanding of how societal emotions are shaped during times of crisis by examining the reflections of technological disruptions on social media.

1.1. Literature Review

With the penetration of digitalization into every aspect of social life, technical failures are no longer merely operational problems; they are acquiring social, emotional, and political dimensions, transforming into instantaneous and widespread public reactions on social media platforms. Understanding this transformation requires an integrated perspective that combines crisis communication theory, sentiment analysis methods, and social media behaviour research. This literature review, written in this context, reveals social media behaviour patterns during crisis periods (events that create sudden and devastating societal impacts such as natural disasters, armed attacks, cybersecurity breaches, and large-scale IT outages), the emotional impact of IT and cyber crises on public opinion, and the key findings of sentiment analysis studies conducted in this field.

Studies examining the content of social media users show that posts are predominantly informational and observational in nature, rather than personal (Naaman et al., 2010). This pattern becomes even more pronounced during times of crisis. Heverin & Zach (2010) analysed Twitter usage during a shooting incident in the Seattle-Tacoma area; they found that informative messages constituted the vast majority of posts and that the platform primarily functioned as a channel for instant status updates. Terpstra et al. (2012) demonstrated that real-time Twitter data can be used as a decision support tool in disaster and emergency crises. Although these studies address different areas, their common conclusion is noteworthy: during a crisis, social media users act not as emotional commentators, but as but as active information sharers. However, some research suggests that emotional biases lie behind seemingly neutral posts. Gaspar et al. (2016) showed that people's emotional responses to unexpected and stressful events cannot be simply categorized as "positive" or "negative"; Different emotions such as fear, humour, solidarity, and the search for information often coexist simultaneously. According to researchers, this complexity is an inevitable feature of communication during times of crisis. Therefore, sentiment analysis tools that rely solely on a positive-negative distinction may be insufficient to fully reflect the true emotional content of crisis communication. The role of humour and irony as coping mechanisms during times of crisis has been examined in detail in recent research. Alkaraki et al. (2024) in a systematic review of social media humour during the COVID-19 pandemic, documented that users resorted to ironic, sarcastic, and humorous content to manage collective anxiety, strengthen social bonds, and regain a sense of autonomy in the face of events perceived as threatening or absurd. This behaviour is directly related to the contexts of IT disruptions, as the deep gap between the mundane technical nature of a malfunction and its devastating consequences in the real world creates conditions highly conducive to ironic expression. Kang et al. (2019) addressed the crisis of the recall of Samsung Galaxy Note 7 phones due to the risk of explosion; The study examined social media posts in South Korea, the United States, and Germany using sentiment and discourse analysis methods. The research revealed that negative emotions were dominant in all three countries, and discussions, despite cultural differences, focused on the "product issue." This finding indicates that the reaction on social media to a technical crisis does not differ significantly from country to country, meaning it exhibits a universal pattern. As a result, the researchers emphasized that companies facing a technical crisis should monitor social media in real-time and develop proactive communication strategies to protect their reputation.

CrowdStrike incident has been primarily discussed in the literature from its technical and organizational dimensions. Banerjee (2024) highlighted a fundamental difference between this outage and typical cyberattacks: the fact that it was the result of a routine software update going wrong, not a malicious attack, and required individual intervention on each computer, made a rapid mass recovery impossible. Mugu et al. (2024) demonstrated that the crisis exposed vulnerabilities in the global software supply chain and lack of oversight in widely used security tools. George (2024) demonstrated that global reliance on a small number of technology companies made large-scale system failures inevitable.

Sayonara and Deemantha (2024) also documented that while the faulty update was rolled back in approximately 78 minutes, it took days to fully repair the affected systems; this clearly shows how quickly an outage can spread but how slowly recovery progresses. On the other hand, none of these studies addressed how the CrowdStrike outage was experienced and reported by ordinary users on social media.

Studies examining social media data from periods of crisis consistently show that neutral emotion prevails during the peak of the crisis. Lwin et al. (2020) examined global emotion patterns on Twitter during the early stages of the COVID-19 pandemic; while fear and sadness were prevalent, a significant portion of the posts remained emotionally neutral. This finding supports the view that people prefer sharing information rather than expressing emotions during times of crisis. In their subsequent study (Lwin et al., 2022), the same researchers conducted a comparative analysis covering five countries and found that emotions change over time. It has been shown that while negative emotions dominate at the beginning of a crisis, positive emotions reflecting hope and solidarity come to the fore as societies become accustomed to the event. Noor et al. (2020) found that seemingly neutral posts actually cluster around specific topics; this finding shows that topic modeling is necessary not only for sentiment analysis but also for a deeper understanding of the content. Gulzar et al. (2023) examined Twitter discourse during the Russia-Ukraine conflict; they observed that the volume of tweets increased sharply immediately after the conflict began, then decreased, and that negative emotion remained dominant throughout the process. This temporal concentration pattern underlines the importance of analyzing social media data collected immediately after a crisis event and strongly supports the approach adopted in the present study. Mirbabaie et al. (2020), synthesizing research on social media crisis communication in the context of Hurricane Harvey and the COVID-19 pandemic, revealed that social media platforms simultaneously serve multiple functions during times of crisis: information gathering, emotional support, political communication, and uncertainty reduction. Trupthi et al. (2018) explained why classifying neutral tweets, which constitute the vast majority of crisis data, is difficult: these tweets often contain important information and emotions, even though they cannot be simply categorized as positive or negative. The researchers suggested that topic modeling should be used in addition to sentiment analysis to uncover this hidden content. Jahanbin et al. (2019) demonstrated that machine learning-based Twitter analysis can be effectively used in the real-time tracking of epidemics. Camacho (2024) extended this approach to the field of cybersecurity and emphasized that monitoring social media with AI-powered tools has become an integral part of corporate crisis management. Bashir et al. (2021) analyzed 13,156 English-language tweets related to the 2017 Khan Shaykhun chemical attack in Syria to examine public sentiment and reactions. According to the findings, 53.7% of the tweets expressed negative sentiment, 33.6% were neutral, and 12.6% conveyed positive emotions. Gulzar et al. (2023) suggests that in crises involving overt violence or physical devastation, negative emotion tends to dominate a pattern that stands in notable contrast to the neutral-dominant discourse observed in infrastructure-based technical disruptions such as the CrowdStrike outage.

2. Method

2.1. Research Type and Design

This study adopts a mixed-method research approach and utilizes sentiment analysis through the Orange Data Mining program. The study incorporates both quantitative and qualitative dimensions: quantitative in that it generates numerical sentiment scores and statistical distributions through computational methods such as VADER, Ekman, Plutchik, and LDA topic modeling; and qualitative in that it interprets and contextualizes these outputs to uncover the underlying emotional orientations and thematic patterns within the dataset. Text mining and machine learning-based sentiment analysis techniques were employed to analyse large-scale and unstructured textual data. Sentiment analysis refers to the automated analysis of unstructured textual data in order to identify, interpret, and classify the emotional tone or polarity expressed in sentences, opinions, or statements (Arsi & Waluyo, 2021). The study follows a cross-sectional research design, aiming to examine users' emotional expressions and discursive tendencies during a crisis event. By focusing on a single crisis period, the research provides a snapshot of public emotional responses and communication patterns reflected in online discourse.

2.2. Universe and Sample

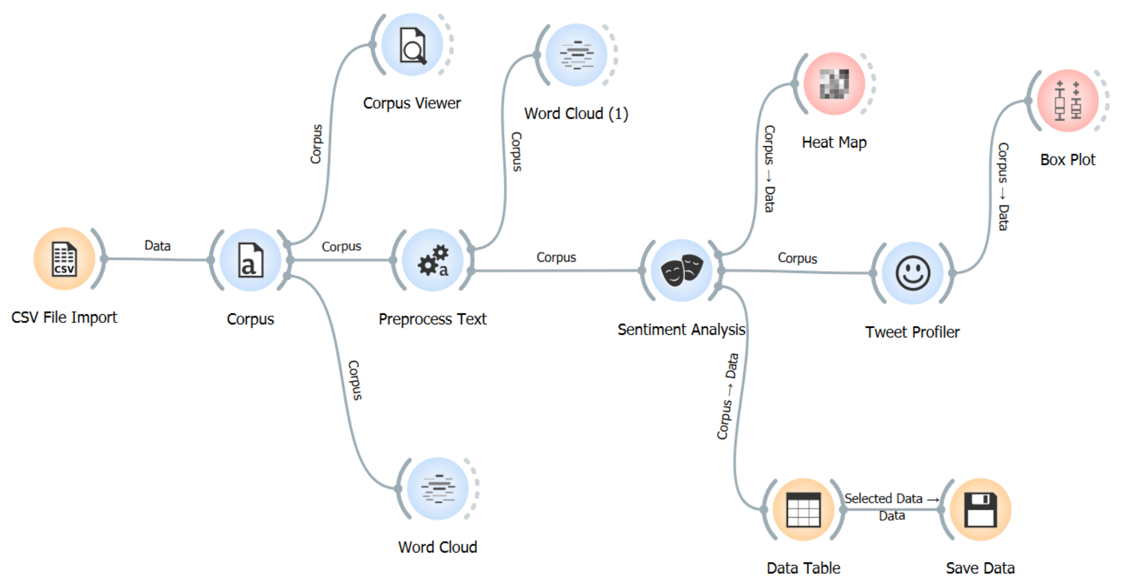
The population of this study comprises publicly available content shared on the X platform concerning the global IT outage triggered by the CrowdStrike incident between July 19 and July 26, 2024. The empirical sample consists of 1,536 English-language tweets posted with the #CrowdStrike hashtag during the specified period. This sampling strategy supports the quantitative assessment of public sentiment and emotional responses during the crisis.

2.3. Research Process

The research process consisted of four sequential stages: data collection, preprocessing, exploratory analysis, and modeling, as illustrated in Figure 1. In the first stage, tweets shared with the #CrowdStrike hashtag within the specified period were collected. In the second stage, raw textual data were preprocessed for text mining by removing noise, standardizing the text, and constructing a structured dataset. Subsequently, exploratory data analysis was conducted to identify dominant patterns and content characteristics. In the final stage, sentiment analysis and topic modeling techniques were applied to uncover emotional orientations and latent thematic structures within the dataset.

Figure 1

Process Map



2.4. Data Collection Tools

Data were collected from the X platform using a web scraping method. This approach was preferred as it allowed to directly oversee and control the data collection process, ensuring that only publicly available tweet texts were included in the dataset. The collection was conducted using the #CrowdStrike hashtag as the search keyword, covering the period between July 19 and July 26, 2024. Only original textual content was retained for analysis. Retweets, duplicated posts, visual elements, hyperlinks, and non-textual content were systematically excluded to ensure analytical consistency and to maintain a focus on user-generated textual expressions. The data analysis process was conducted using the Orange Data Mining software. Orange is a Python-based, open-source machine learning and data mining software that incorporates a wide range of analytical components, including text mining, sentiment analysis, and topic modeling. Its widget-based architecture enables the analytical process to be conducted in a systematic and visually traceable manner.

2.5. Data Analysis

In the data analysis process, all tweet contents were first compiled into a corpus. Subsequently, text preprocessing steps were applied. During the exploratory analysis stage, the overall structure of the dataset was examined using word clouds, heat maps, and tweet profiling tools. In the sentiment analysis stage, the VADER (Valence Aware Dictionary and Sentiment Reasoner) model was employed to identify the emotional orientations expressed in the tweets. In addition, the Ekman and Plutchik emotion models were utilized to provide a more detailed classification of emotions present in the tweets. In the final stage of the analysis, Latent Dirichlet Allocation (LDA)-based topic modeling was applied to uncover latent themes and discussion topics within the tweets.

2.6. Ethical Consideration

The data used in this study consist of publicly available content shared by users on the X platform. During the research process, user identity information, usernames, and personal data were excluded from the analysis. The study was conducted in accordance with data privacy and ethical research principles, and only anonymized textual content was used.

3. Findings

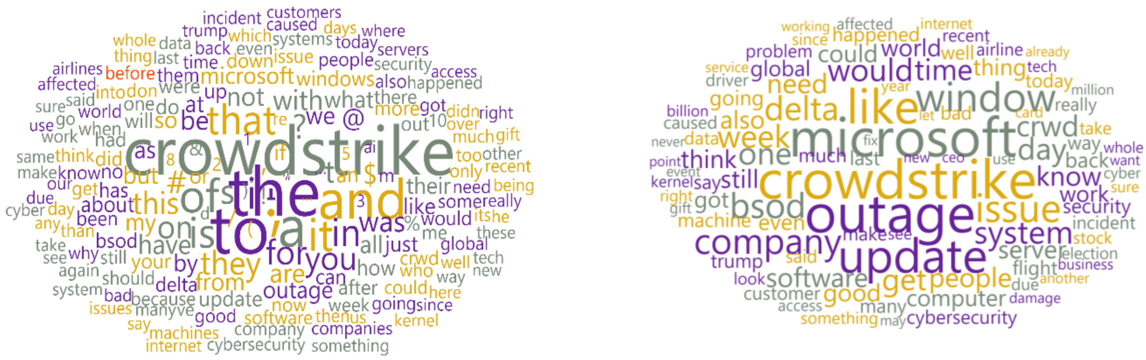
Since the texts retrieved from X are in unstructured form, they need to be converted to structured form using text mining. For this purpose, a pre-processing process is performed. Pre-processing of the input data is a crucial phase in the classification process. During this stage, the dataset undergoes normalization and preparation, which ensures the classification algorithm operates efficiently and yields effective results in minimal time (Jahanbin et al., 2019). The dataset undergoes various processes such as correction, imputation of missing data, removal of duplicate entries, transformation, integration, cleaning, normalization, and dimensionality reduction (Kahya 2021, p.12). This step is highly important for enhancing the effectiveness of the analysis and consists of several stages. Transformation, Tokenization, normalization and Filtering.

The Transformation step involves converting the texts into a standardized and consistent format for analysis. At this stage, tweets are first transformed into lowercase. Then, accents and special characters within the text are cleaned, HTML tags and codes are removed, and URLs are extracted. All of these processes were applied to the dataset during this stage of the study. Tokenization is a fundamental step in analyzing text data. This process helps to extract the meaning of the text by examining the sequence of words. The primary goal of tokenization is to separate words or groups of words within a sentence. Tokenization, enables the removal of meaningless words, the removal of unnecessary characters, that is, the removal of noisy data, and prepares the basis of the analysis since tokens are needed for sentiment analysis. Normalization translates words into a distinct form, allowing for the recognition of words that have the same meaning (Welbers et al., 2017). In this way, the data size is significantly reduced, and the focus is on the essential part. Filtering stage, words that do not make a meaningful contribution to text classification are removed from the text. These include stop words (e.g., pronouns, articles, prepositions such as “the,” “a,” “about,” “we,” “our”), noise elements (such as punctuation marks and special characters), and offensive or inappropriate language (including slang or vulgar terms).

After completing the Pre-Process step, a word cloud is created to visualize the key concepts and focus areas of the dataset. This visualization tool expresses word frequency through visual arrangements such as size and colour, providing a quick and understandable summary of the dataset's content. The sizes of words change in proportion to their frequencies. Word Cloud before and after the pre-process is seen in Figure 2. As it was before the Pre-Process was done, "." (1774), the (1493), "," (1092), and, to, a, of, etc., while there are words and characters that do not have a meaning on their own. After the pre-processing step, more meaningful and focused words emerged, with 'Crowdstrike,' 'outage,' 'Microsoft,' and 'update' being the most frequently used. The inclusion of words such as delta, customer, company, flight, airline also gives clues about the sectoral areas caused by the Crowdstrike outage.

Figure 2

Word Cloud Before and After Pre-Process



Following the Word Cloud process, the sentiment analysis stage is carried out. The widget process for sentiment analysis in the Orange program is presented in Figure 1. One of the most widely used methods for performing sentiment analysis on social media texts is VADER (Valence Aware Dictionary and Sentiment Reasoner), which is a rule-based model (Hutto & Gilbert, 2014). This model is considered the gold standard in the field of text analysis due to its coverage of lexical features used in the analysis of emotional expressions on social media (Bonta et al., 2019). VADER generates a single, normalized compound sentiment score for each text, ranging from -1 to +1, which is the sum of all positive and negative scores. This score quantitatively represents the text's overall emotional state and is evaluated using classification thresholds: a score of 0.05 and above is considered positive, -0.05 and below is negative, and anything between these two values is considered neutral (Mir et al., 2022).

In this study, the sentiment scores of all tweets were averaged to determine the overall sentiment trend in the dataset (Table 1). This approach focuses on capturing the general emotional orientation of users rather than analysing each tweet individually. By averaging sentiment scores, the analysis provides a comprehensive and holistic overview of public perception during the examined event, allowing dominant sentiment patterns to be clearly observed.

Table 1

VADER Sentiment Analysis Average Score

Emotion Category	Average Score
Positive	0,0862
Negative	0,0992
Neutral	0,8145
Compound	-0,0517

According to the results of the VADER analysis in the table, the sentiment of the tweets examined stands out in three main points. First, the neutral sentiment score (0.8145) has the highest average, indicating that most of the posts in the dataset do not have a distinct emotion and consist more of informative, current, or newsworthy content. Second, although the negative (0.0992) and positive (0.0862) scores are close to each other, the slightly higher average for negative expressions suggests that negative expressions are slightly more dominant in tweets with emotional content. Finally, the composite score of -0.0517, which indicates the overall sentiment of the entire data set, indicates that the overall trend in tweets has shifted towards a slight negativity, as it is just below VADER's threshold of -0.05. These findings highlight that despite the predominance of neutral content, the sum of emotional responses weighs on the negative side.

Table 2 provides examples of tweets that caused the dataset to exhibit a generally negative trend (compound: -0.0517). These texts contain values from the VADER model regarding its interpretation of social media language and technical terms. Upon examining these examples, it can be seen that VADER considers multiple factors when detecting negative sentiment. For example; "Nasty people are scared their nasty man will lose." The word "nasty" for his tweet is a word with a high level of negativity, and its use more than once affects the intensity of the emotion. Looking at the examples, a negative sentiment is also observed in tweets containing the term "BSOD" (Blue Screen of Death). BSOD indicates a negative situation in computer terminology, thus tilting the overall sentiment tone towards negative. Similarly, negative words such as "blame" and "threat" also convey negative sentiment.

Table 2

Examples of Tweets with Negative Sentiment

Content	positive	negative	neutral	compound
Nasty people are scared their nasty man will lose.	0,0000	0,7190	0,2810	-0,9153
Blame Crowdstrike...	0,0000	0,7060	0,2940	-0,3400
misspelling of BSOD	0,0000	0,6630	0,3370	-0,6037
Bsod flip	0,0000	0,7620	0,2380	-0,4939
No worries friend … auto wrong strikes us all	0,1900	0,6310	0,1790	-0,7506
CrowdStrike threat	0,0000	0,7730	0,2270	-0,5267

Table 3 provides examples of tweets containing neutral sentiment. Upon reviewing these tweets, we can see the presence of short sentences or not highly relevant to the main topic. General informational content and information about sectoral companies which are affected are categorized as neutral. Taking the example tweet "Separately, CrowdStrike reportedly offered $10 Uber Eats gift cards to some of its partners impacted by the outage. Some who received the vouchers found they were not redeemable, and the offer has since reportedly been rescinded," can be said that despite a high neutral sentiment of 0.9170, it also shows a positive tendency with a compound score of 0.4902. This small positive score might be due to a single word like "offered" which carries a positive connotation.

Table 3

Examples of Tweets with Neutral Sentiment

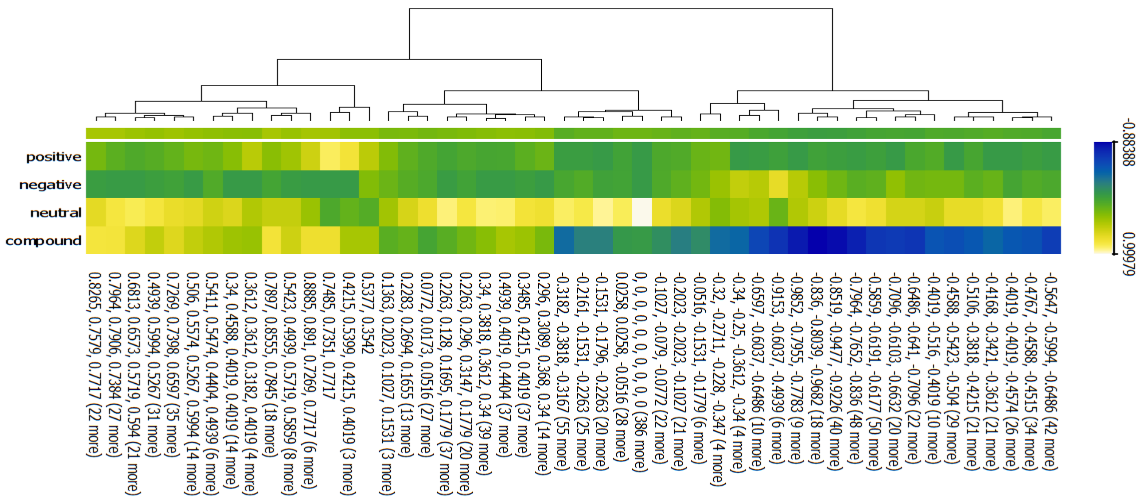
Content	positive	negative	neutral	compound
I wonder how much the crowdstrike meltdown was related to the oopsie in the Venezuelan elections	0,0000	0,0000	1,0000	0,0000
Not working	0,0000	0,0000	1,0000	0,0000
It just can't	0,0000	0,0000	1,0000	0,0000

CrowdStrike CEO George Kurtz says the company has recovered 97% of Windows systems impacted by a recent IT outage. The exec credited the quick turnaround to the development of a new automatic recovery technique. In the meantime, Microsoft has published its own technical deep dive	0,0560	0,0000	0,9440	0,3612
The Crowdstrike debacle was the first step of the Dems to set up their ability to manipulate the results ovf the election in November.	0,0910	0,0000	0,9090	0,3182
Delta hires a law firm to seek damages from Microsoft and CrowdStrike after a massive cyber outage disrupted 6,000 flights and left travelers stranded. The U.S. Transportation Department also launches an investigation.	0,0000	0,0910	0,9090	-0,4404
Trying to see how I can make some money off crowdstrike stock tanking I need ask my AI stock bot havent read any charts in a while or see what the stock gurus are saying idk if it's going down more or this is the bottom	0,0000	0,0320	0,9680	-0,1027
Separately, CrowdStrike reportedly offered $10 Uber Eats gift cards to some of its partners impacted by the outage. Some who received the vouchers found they were not redeemable, and the offer has since reportedly been rescinded.	0,0830	0,0000	0,9170	0,4902

The numerical values obtained are also observed in the heat map showing the distribution of sentiment scores (Figure 3). A heat map is a graphical technique used to visualize the values of numerical attributes within a two-dimensional matrix. By positioning class variables and attributes on the x and y axes, a heat map enables us to identify where attribute values are strongest and weakest. This approach is particularly useful for finding typical characteristics associated with each class. This map presents the distribution of sentiment scores calculated by VADER for each text as a whole. The color scale of the map shows the lowest values in dark blue and the highest values in yellow. According to the heatmap, the most dominant sentiment tone in the dataset is neutral. The entire "neutral" column is covered in yellow, representing high scores, proving that the vast majority of texts do not convey a strong emotional tone. The presence and distinct clustering of dark blue colours on the map suggests that texts with negative sentiment come together to form a more pronounced density. This finding supports the reason why the compound score average was slightly negative (-0.0517). Although neutral texts are dominant, a small number of strong negative texts negatively affect the overall average.

Figure 3

Heat Map

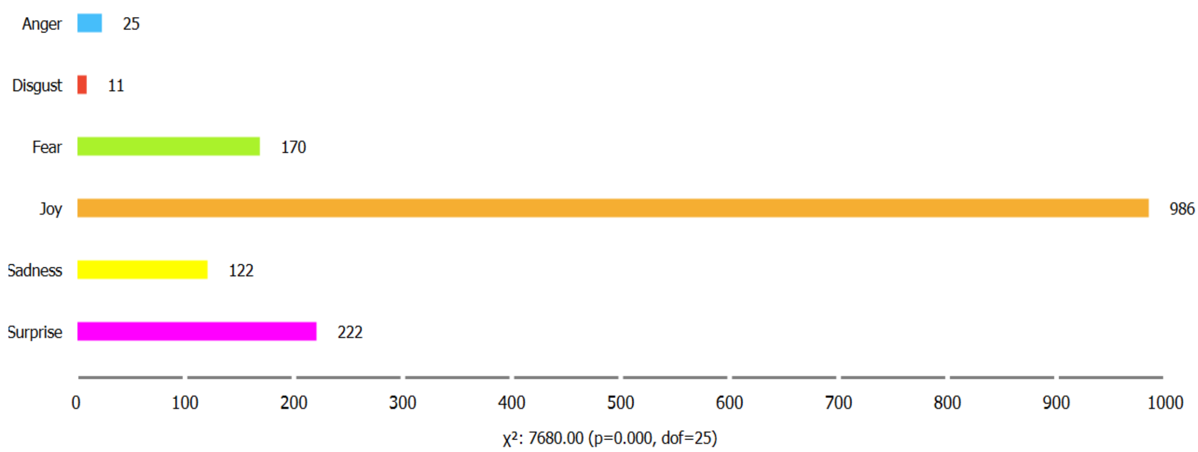


Through the Tweet Profiler, sentiment information for each tweet can be extracted from the dataset, and sentiment analysis can be performed using various classification techniques. The widget supports three different classifications of emotions: Ekman, Plutchik, and the Profile of Mood States (POMS) At this stage, Ekman and Plutchik algorithms were used. Both algorithms classify different numbers of emotions. According to (Plutchik, 1980) these are: anticipation, acceptance, joy, surprise, anger, disgust, fear, sadness. Ekman (1982) distinguishes joy, surprise, anger, disgust, fear, sadness.

Figure 4 presents the distribution of emotions identified from 1,536 tweets analysed using the Ekman emotion classification algorithm. The results indicate that the majority of tweets were dominated by the emotion of joy (64%), followed by surprise (14%), fear (11%), and sadness (8%), while anger and disgust were observed at relatively low levels. These findings suggest that although positive emotional responses were predominant, the presence of emotions such as surprise, fear, and sadness reflects a diverse emotional reaction among users during the examined event.

Figure 4

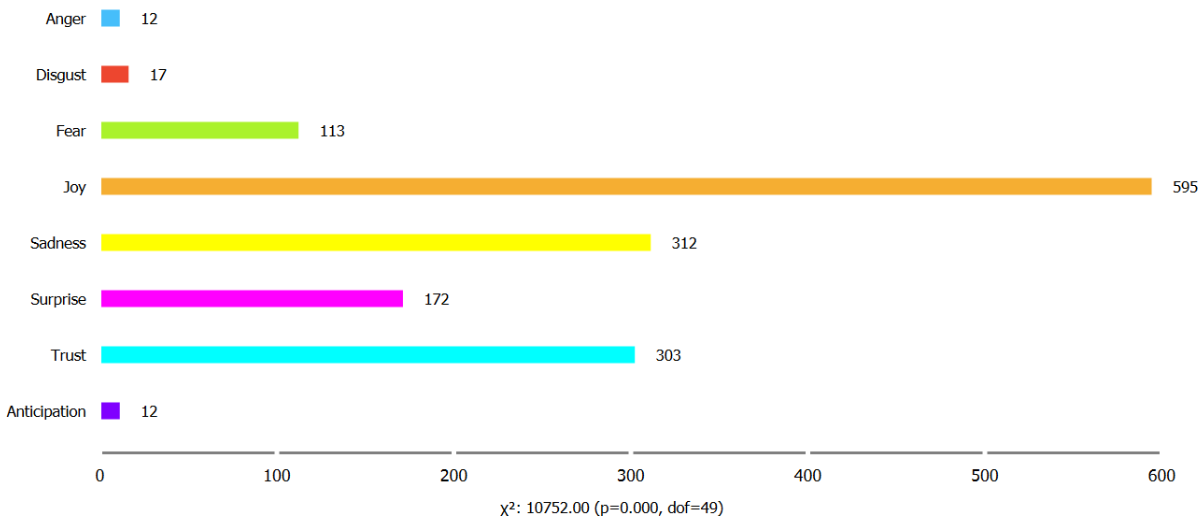
Data Emotion Based on Ekman



In Plutchic, emotions are categorized more, with the addition of feelings of trust and anticipation. According to the Plutchic Algorithm shown in Figure 5, the highest number are; 595 are joy (39%), 312 are sadness (20%), 303 trust (20%), 172 surprise (11%), 113 fear (7%). While the Ekman model has a more general category of emotions, the Phutchic model has a more detailed classification of emotions. According to this model, it is seen that joy is still the most common emotion, but also the feelings of sadness and trust are at a level that cannot be underestimated. These differences can be attributed to the differences in the vocabulary used by each model for sentiment analysis.

Figure 5

Data Emotion Based on Plutchic



According to the Ekman model, positive emotions (joy, surprise) are 78% and negative emotions (anger, disgust, fear and sadness) are about 22%. According to the Plutchic model, positive emotions (joy, surprise, trust, anticipation) are approximately 70% and negative emotions are 30%. The feeling of "joy" may not necessarily mean "happiness" here; positive anticipation can also carry subordinate meanings such as relief or contentment. According to the Ekman and Plutchic Model, sample tweets by sentiment are shown in Table 4.

Table 4

Tweet Examples of Emotion Classification: Plutchik and Ekman Model

Plutchic Model	**Emotion**
Good. Now they know what to do.	Trust
Let's go crowdstrike	Trust
Without a doubt. Fake…fake…fake. Time for some independent polling! Make sure polling data server security is NOT @CrowdStrike !!!	Trust
Although I acknowledge the risks, I think they are a bit overstated	Trust
As a shareholder, I am currently in great distress because CrowdStrike has to spend a lot of time preparing a legal team for Delta Airlines' lawsuit. In the investment industry, we look at a time frame of up to 5 years, so shouldn't there be some sort of strategy in place?	Sadness
Yeah their system is still badly affected by crowdstrike glitch	Sadness
I've heard of pizza parties for employees, but for customers too? RIP Crowdstrike	Sadness
I hear that's what happened to Crowdstrike.	Sadness
Ekman Model	**Emotion**
You must work at CrowdStrike	Joy
Is it cold? It's 18492 degrees here	Joy
Wait, did you start working for Crowdstrike?	Joy
I have a support ticket in place and working through the issue hopefully to be resolved.	Joy
I'm surprised Delta and all the other companies affected aren't suing Crowdstrike	Surprise
Just means we don't know. That's not comfortable? It is actually more terrifying? CrowdStrike?	Surprise

is this related to the #crowdstrike issue? or is a normal behavior from Wizzair?	Surprise
I am stronger than anxiety	Fear
CrowdStrike is finished. Such poor response like that after a catastrophe on their part will make their legal situation extremely dire.	Fear
AI? This is really scary. WTF is going on in the Whitehouse rn? Crowdstrike, assassinations.	Fear

Thus far, the study has concentrated on the sentiment analysis of tweets. The next stage shifts the focus toward exploring the underlying themes discussed in these tweets. While sentiment analysis uncovers the emotions expressed within the text, topic modeling identifies the main subjects around which the discourse is constructed (Blei et al., 2003). As highlighted by Trupthi et al. (2018) one of the key challenges in Twitter sentiment analysis lies in the predominance of neutral tweets, which are often more difficult to classify than positive or negative ones. Topic modeling serves as a complementary analytical approach that can help address this challenge by providing deeper insights into the content of neutral tweets.

Topic modeling is a method used to identify and examine clusters of topics within a corpus. It relies on Latent Dirichlet Allocation (LDA), a generative technique that produces sets of words from a dataset, where each set reflects terms that are associated with a specific topic group (Alghamdi & Alfalqi, 2015). This model contains information that does not have predefined labels (Zhai & Massung, 2016). Topic modeling is utilized to reveal underlying semantic structures embedded in textual data (Ghosh & Guha, 2013). The model employs computational methods to uncover thematic patterns (topics), helping users to locate, organize, and make sense of substantial amounts of unstructured text (Qiao & Williams, 2022). Table 5 shows the results of the topic modeling analysis. The number of groups in the Orange program is determined as 10. When we look at the underlying issues of tweets, they can be evaluated under 5 main headings.

1- Technical and System Problems: Topics consisting of keywords such as BSOD, computer, window, server, software focus on technical failures and system outages experienced by users. This category directly addresses the technical details of the incident and the user experience. Topics 3 and 4 can be given as examples.

2- Corporate and Financial Repercussions: Topics involving words like stock, company, crwd, security reflect discussions about the financial implications of the bug on CrowdStrike. Its stock value, and how the company's reputation in cybersecurity has been affected. Topic 5 can be an example.

3- Real-World Implications: A topic with words like delta, flight, get, access draws attention to the tangible consequences of the technical problem. Especially how it disrupts the operation of large systems like airlines. Topic 10 can be given as an example.

4- Negative Emotions and Comments: The topic, which includes expressions such as bad, issue, outage, expresses users' dissatisfaction with the error, disappointment, and generally negative emotions. This title, unlike the informative language on other topics, carries an emotional content. Topic 7 example

5- Political Agenda: The inclusion of words like trump and election suggests that this technical issue is quickly becoming associated with the political agenda or part of political discussions. This is an interesting testament to how an event on Twitter can move out of its technical context and into broader social and political conversations. Topics 2, 8 and 9 can be given as example.

Table 5

Topic Modelling Results

No	Topic Keywords
1	crowdstrike, like, driver, work, could, look, since, issue, day, use
2	crowdstrike, security, much, data, need, stock, machine, trump, update, world
3	bsod, computer, crowdstrike, even, got, work, like, right, window
4	crowdstrike, outage, crwd, company, global, cybersecurity, system, software, recent, caused
5	crowdstrike, one, people, server, time, also, problem, like, many, company
6	crowdstrike, week, issue, system, last, card, gift, company, said
7	crowdstrike, bad, would, today, see, issue, year, outage
8	crowdstrike, would, customer, back, think, good, know, never, trump
9	crowdstrike, window, update, event, still, happened, day, week, way, election
10	crowdstrike, delta, flight, get, going, access, microsoft, outage

4. Discussion

In this research, the sentiment of tweets posted with the hashtag #Crowdstrike following the escalation of the CrowdStrike outage into a crisis was examined. According to the VADER algorithm, the majority of the content displayed a neutral sentiment tone. These neutral posts can be explained by users' tendency to provide information about the incident, ask questions, make situational assessments, or share short statements that do not contain emotional expressions. This finding is closely related to the duration and nature of the crisis. Although only 1 hour and 18 minutes elapsed between the release of the faulty update and its withdrawal by CrowdStrike (Banerjee, 2024; Mugu et al., 2024) the need for millions of computers to be manually restarted meant that the full recovery process took hours or even days (Sayonara & Deemantha, 2024). This suggests that, during the first week after the incident, users adopted a predominantly neutral approach centered on information flow and situational reporting, rather than expressions of initial shock or anger. This situation explains that tweets shared during crises or disasters differ from those posted under normal circumstances, being more information-oriented, as highlighted by Naaman et al. (2010) and Terpstra (2012). Similarly, Heverin & Zach (2010) in their study of tweets related to an accident, conducted a content analysis and reported that the majority of posts contained informational messages. These results further demonstrate that, following the immediate impact of a technical crisis, public responses quickly stabilize and shift focus from emotional reactions toward seeking and sharing information related to the event. As stated by Mirbabaie et al. (2020), in situations where there is too much information or information is unclear, people seek information on social media to fill knowledge gaps. In the context of the CrowdStrike outage, the technical complexity of the incident and the uncertainty surrounding its cause and scope during the first days may have further reinforced this information-seeking behavior, contributing to the dominance of neutral content in the dataset.

Again, according to the VADER algorithm, negative scores slightly higher than positive scores indicate that words with negative meanings such as "problem," "slow," "late". These emotions reveal that users who experienced concrete issues—such as the cancellation or alteration of their scheduled programs immediately after the incident—expressed their negativity more intensely on an emotional level. This finding demonstrates how a technical crisis can lead to strong negative emotional reactions as it affects daily life.

In order to provide a comprehensive analysis of emotional responses, the study also employed analyses based on Ekman and Plutchik models as well as topic modeling method. According to the analyses conducted using the Ekman and Plutchik models, it was observed that while the emotion of joy was relatively high in the tweets shared during the outage, emotions such as surprise, fear, sadness, and trust were also prominent. The detection of "joy" by the Ekman and Plutchik algorithms may have stemmed from the presence of specific keywords in the texts (e.g., "solved" or "fixed"), which reflect satisfaction with the resolution of infrastructure problems, or in some cases, from the ironic use of language. This indicates that users tend to use positive language, but there are also emotions such as sadness, surprise, fear and trust underlying this positive expression. Emotional reactions are often complex during times of crisis (Gaspar et al., 2016). Similar results are found when the literature is examined. For example, in the study on sentiment analysis of tweets during the COVID-19 period (Lwin et al., 2020), emotions such as fear, anger, sadness, and joy are at the forefront and emotions such as fear and hope are dominant. These findings further support the multidimensional and variable nature of emotional reactions in times of crisis.

It is important that the research is also carried out with topic modeling analysis. This is because it is critical not only to understand public feelings but also to know which topics are being discussed. Such analyses can provide valuable feedback and contribute to the introduction of new regulations and standards for companies. Although there are 10 main topics in the topic modeling analysis, it is seen that only one topic (Topic 7) contains words that express distinctly negative emotions (e.g., bad, outage). This finding indicates that negativity is not a widespread theme in the overall discussion but is instead concentrated in a small number of topics that convey strong and impactful negative emotions. This outcome is consistent with the VADER algorithm. Although most tweets are classified as neutral in the VADER analysis, that small negative trend in the total score, higher than positive, is due to this single and strong negative thread. This reveals that the negativity in the dataset is quantitatively low but qualitatively intense.

Some of the topics identified in the topic modeling analysis do not exhibit emotional expressions but instead represent more informational and data-oriented discussions. Under the heading of Technical and Financial Issues (heading 1 and 2), topics containing keywords such as bsod, outage, system, security, company, stock focus on the technical details of the incident and its financial implications. This type of speech usually uses neutral and objective language. It's an indication that users are tweeting more about discussing what the problem is, when it was resolved, or how it impacted the company, rather than expressing their feelings. The high score of 0.8165 in the VADER analysis is precisely due to the dominance of tweets on these topics. This finding demonstrates that a large portion of the dataset is more informative than emotional in nature.

Although "Joy" wasn't a prominent theme in the topic modeling results, the fact that "joy" is the most dominant emotion in the sentiment analysis suggests that reactions to a problem, along with humorous and sarcastic messages, are often included. Tweets containing words such as "update" or "fixed", which are intended to resolve the Crowdstrike issue, can be combined with words or emojis that express joy, such as "finally!" or "so happy!" While the main subject of these tweets is technical, the underlying sentiment convey is joy. Some users may express the seriousness of the incident with joy by mitigating it through humour. The use of humour during crisis periods is not uncommon on social media platforms. Research indicates that humour functions as a coping mechanism that helps individuals navigate stressful situations, maintain social cohesion, and promote well-being during periods of uncertainty (Gaspar et al., 2016; Alkaraki, Alias & Maros, 2024). According to El Maarouf (2025) humour functions as a coping mechanism during times of crisis, serving to alleviate the anxiety that arises from a sense of powerlessness in the face of unfolding events. In the case of the CrowdStrike outage, the widespread impact of the disruption appears to have created a common ground among users, facilitating the use of humour as both a coping strategy and a form of social solidarity.

In such incidents that reach the global level, it is clearly seen that a technical problem is not limited to its own field, but spreads to much wider social, political and financial discussions. In addition to the expected aspects of the incident (BSOD, server issues), user experience (real-world implications), and corporate repercussions (stock, reputation), it is noteworthy that political keywords such as Trump and the election were also prominently featured in the topic model analysis. This situation reveals the power of social media to take an event out of its technical context and instantly make it a part of a social and political discussion. These finding sheds light on the cybersecurity crisis not just technical glitches but multi-layered events that intersect with political agendas and overall moods. As Mirbabaie et al. (2020) points out, the use of information systems is not limited to crisis management; it is also influential in areas such as political communication, social movements, marketing, media literacy, and education. The prominence of political keywords such as Trump and election in the topic modeling results can be partly attributed to a specific contextual factor: the CrowdStrike outage occurred on July 19, 2024, coinciding with the final night of the Republican National Convention, during which Donald Trump formally accepted his presidential nomination. This temporal coincidence likely contributed to the rapid intersection of the technical incident with political discourse on social media.

5. Conclusion

This study examined how a large-scale IT infrastructure failure was experienced, communicated, and emotionally processed by the public on social media. The findings reveal that public discourse during the crisis was predominantly neutral in tone, consistent with the crisis communication literature suggesting that individuals prioritize information-seeking and situational updating over emotional expression during sudden disruptions (Lwin et al., 2022; Naaman et al., 2010). At the same time, multi-dimensional emotion analyses using Ekman and Plutchik models uncovered a more complex emotional landscape beneath this neutral surface one in which joy, surprise, fear, and sadness coexisted simultaneously. The unexpectedly high joy scores, interpreted in conjunction with the irony and sarcasm limitation of lexicon-based tools, suggest that users resorted to humour and ironic expression as coping mechanisms (Alkaraki et al., 2024). Furthermore, topic modelling revealed that the outage rapidly transcended its technical boundaries, intersecting with political discourse a pattern likely amplified by the coincidence of the outage with a major political event on the same day.

These findings show that the study offers significant contributions from both theoretical and practical perspectives. Theoretically, the study contributes to the literature by enhancing our understanding of how social media users respond during IT crises. The findings indicate that infrastructure-based technical disruptions produce a response pattern that differs from the highly negative emotional patterns commonly observed in violent or politically charged crises. In other words, during technical crises such as the CrowdStrike incident, user responses are not limited to anger, fear, or sadness; they also include more neutral and multidimensional reactions such as seeking information, following situational updates, sharing content, and using humour (Kang et al., 2019; Gulzar et al., 2023; Bashir et al., 2021).

The study demonstrates how Orange Data Mining software can be systematically applied to a sentiment analysis process that brings together VADER, Ekman, Plutchik, and LDA topic modeling within a single analytical framework, confirming that this combination of models offers a comprehensive and complementary approach to understanding public sentiment during IT crises. To the best of the author knowledge, this study is the first academic work to examine the CrowdStrike IT outage through sentiment analysis using Orange Data Mining software, filling a notable gap at the intersection of IT crisis analysis and machine learning-based text mining. The findings reveal how public emotions shift rapidly during a large-scale IT crisis and how a purely technical disruption can quickly evolve into broader social and political discourse on social media, offering concrete and actionable insights for IT crisis management and organizational decision-making.

6. Recommendation

Based on these findings, several recommendations can be offered for policymakers, practitioners, and future researchers. Technology companies and IT service providers can integrate sentiment analysis tools — such as VADER and Ekman-based models — into crisis management and decision support systems to monitor public reactions in real time. This approach enables the early detection of sudden spikes in negative sentiment and supports a proactive rather than reactive crisis communication strategy. For communication and public relations professionals, the findings of this study carry a critical message: during IT crises, the public needs accurate and clear information before emotional reassurance. Crisis communication strategies should therefore be grounded in timely and consistent information flow, avoiding messages that may amplify ambiguity or fuel public anxiety. Governments and regulatory bodies can establish standardized communication protocols to ensure timely and transparent information dissemination during large-scale IT disruptions. Additionally, policymakers can encourage collaboration between public institutions and private technology firms to strengthen digital resilience and minimize societal impacts during global IT crises. For future research, it may consider employing longitudinal research designs to examine how public sentiment evolves before, during, and after IT crisis events. Comparative studies across different countries or crisis types could also provide deeper insights into cultural and contextual differences in emotional responses.

7. Limitations

There are some limitations that should be considered when interpreting the findings of this study. First, the dataset consists of 1,536 tweets, and as with any research, the generalizability of the findings should be evaluated within certain boundaries in terms of sample size. Although this represents a substantial cross-sectional snapshot of the relevant public discourse, it cannot be assumed to capture every tweet published within that timeframe. Accordingly, the findings should be interpreted as reflecting the observable patterns within this dataset rather than the totality of online reactions to the event. The dataset is limited to English-language tweets shared under the #CrowdStrike hashtag, which excludes reactions from non-English-speaking users and therefore limits the cultural and geographical representativeness of the findings. The lexicon-based models employed in this study — VADER, Ekman, and Plutchik classifiers — assign sentiment scores based on word-level valence without performing contextual inference. As a result, ironic or sarcastic expressions are liable to be systematically as positive. In a crisis context such as the CrowdStrike outage, technically positive resolution terms ("fixed," "solved," "finally") and ironically used phrases ("great job," "well done") may have inflated joy and positivity scores beyond what genuinely reflects user intent. This limitation is acknowledged as a potential source of bias in the emotion classification results. Future studies are encouraged to employ larger datasets, extend the time frame of analysis, and conduct comparative cross-cultural studies to provide a more comprehensive understanding of public sentiment during large-scale IT crises.

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