

# Sentiment and Emotion Analysis of Public Discourse on ChatGPT Using VADER Sentiment Analysis

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## ABSTRACT

The rapid emergence of artificial intelligence (AI) technologies has ignited global discussions, particularly around ChatGPT, an AI tool designed to transform how humans interact with digital systems. This study explores public sentiment and emotional reactions towards ChatGPT during its initial launch period, analyzing a dataset of tweets sourced from Kaggle. Leveraging the VADER sentiment analysis algorithm, the research categorizes user reactions into positive, negative, and neutral sentiments, while also identifying key emotional tones such as joy, fear, and skepticism. The findings reveal that positive sentiment prevailed, reflecting excitement about ChatGPT's innovative capabilities, while concerns regarding ethics and job displacement gradually surfaced, underscoring the dual nature of public opinion. Through visualizations such as bar charts, time-based sentiment trends, and word clouds, the study highlights the dynamic engagement of users with ChatGPT and its broader implications for society. Key insights suggest that public perceptions of AI are influenced by its perceived utility, accessibility, and ethical considerations. While the study demonstrates the efficacy of VADER in capturing sentiment trends, it also acknowledges limitations, including the inability to detect sarcasm or nuanced emotional expressions. The implications of this research extend to AI developers, policymakers, and researchers, emphasizing the importance of public engagement strategies that address ethical concerns and build trust. Additionally, the study contributes to the growing body of knowledge on digital society, offering a framework for understanding how emerging technologies shape public discourse. Future research could focus on comparative analyses across different social media platforms or delve deeper into the evolution of public sentiment over time. By unraveling these complexities, this study aims to guide the responsible development and deployment of AI technologies in an increasingly interconnected world.

**Keywords** ChatGPT, AI Sentiment Analysis, Public Opinion, Digital Society, VADER

## Introduction

The rise of artificial intelligence (AI) technologies, particularly ChatGPT, has ignited a significant global discourse marked by both enthusiasm and apprehension. This duality in public perception is essential for understanding the broader societal implications of AI developments. While AI offers transformative potential across various sectors, it also raises important concerns, particularly around employment, privacy, and ethical considerations [1], [2], [3]. Research highlights how media narratives around AI can amplify these concerns, often focusing on the risks associated with these technologies. Such framing plays a critical role in shaping public discourse and pushing a societal agenda that emphasizes caution and calls for regulation [4], [5]. In the specific case of ChatGPT, reactions have been mixed. Initial discussions on platforms like Twitter showcased a broad spectrum of opinions, from

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excitement about its potential applications to fear about its implications for privacy and job security [2]. These contrasting views provide valuable insights into how new technologies like ChatGPT are perceived by different segments of the public. By analyzing public discourse through sentiment and emotion analysis, we can better understand the factors driving these responses. Tools such as VADER sentiment analysis are particularly well-suited for this purpose, offering a quantifiable method to assess the sentiment embedded in large volumes of text data, such as social media discussions [4].

Sentiment analysis not only allows researchers to classify public opinion as positive, negative, or neutral but also uncovers deeper emotional tones, revealing underlying public concerns or excitement. This approach, when applied to the discourse surrounding ChatGPT, can provide critical insights into how AI is shaping societal attitudes, influencing perceptions, and potentially guiding future regulatory and policy decisions [5]. Through such analysis, we gain a clearer picture of the emotional and psychological impact AI technologies have on the global public.

Understanding public sentiment is increasingly recognized as essential for developers, policymakers, and businesses, particularly in the context of rapidly evolving AI technologies like ChatGPT. The integration of AI into daily life necessitates a nuanced comprehension of public attitudes and concerns, as these perceptions can significantly influence the trajectory of AI development and its acceptance in society [6], [7], [8]. For instance, Müller and Bostrom highlight that understanding public sentiment is crucial for guiding responsible AI development and informing policymaking, especially as AI technologies continue to shape various sectors. Without a deep understanding of these societal reactions, the development of AI technologies may encounter resistance or be misaligned with public expectations [6].

Research shows that public perception of AI is shaped by a complex interplay of admiration for its potential benefits and apprehension regarding its risks [8]. While AI promises improvements in efficiency, healthcare, and many other fields, it also raises concerns about job displacement, privacy breaches, and ethical dilemmas. This dichotomy is evident in the public's discourse on platforms like Twitter, where opinions about AI technologies like ChatGPT reflect both excitement and fear. Public sentiment can be influenced by various factors, including the framing of AI in the media, with coverage often emphasizing its potential dangers [5].

The framing of AI in media narratives plays a pivotal role in shaping public attitudes, often highlighting risks associated with AI technologies, which can lead to a societal agenda that prioritizes regulation and caution [4]. This complex dynamic reveals how discourse surrounding AI, particularly ChatGPT, is not simply a reflection of technological capabilities but is also deeply intertwined with societal concerns and values. As such, analyzing public sentiment provides valuable insights into the broader societal discourse surrounding AI, shedding light on how emerging technologies influence perceptions and shape public opinions.

While the rise of ChatGPT has prompted significant public discourse, there remains a notable gap in systematic analysis of the sentiment and emotion expressed by users during the early phase of its release. Public reactions to ChatGPT, particularly on social media platforms like Twitter, have ranged from excitement to skepticism, yet these responses have not been thoroughly explored through a structured analytical lens. Understanding how people perceive the capabilities of AI, its ethical implications, and its potential impact

on society is essential for informed decision-making by developers, policymakers, and businesses. This lack of systematic sentiment analysis limits our understanding of the broader societal conversations surrounding AI technologies, especially in their nascent stages. By focusing on the public's immediate reactions to ChatGPT, this study aims to fill this gap.

The objective of this study is to analyze the sentiment and emotion of public tweets about ChatGPT using the VADER sentiment analysis tool. VADER, an acronym for Valence Aware Dictionary and sEntiment Reasoner, is particularly effective for analyzing informal social media content. It assesses both the polarity (positive, negative, or neutral) and the intensity of sentiments expressed in the text. This study applies VADER to a dataset of tweets discussing ChatGPT, offering a clear, quantifiable analysis of how the public feels about this revolutionary AI tool. By analyzing these emotions and sentiments, the study aims to provide a snapshot of societal attitudes toward AI and ChatGPT in particular, contributing to ongoing debates about AI's role in society.

This study offers significant insights into how AI technologies, specifically ChatGPT, are received by the public. It highlights the initial emotional and sentiment-driven reactions that shape societal discourse and could influence the development and integration of AI tools in the future. The findings provide valuable data not only for AI developers, who can use these insights to refine their products and address public concerns, but also for digital society researchers seeking to understand the broader impact of AI on public perception. By analyzing public sentiment at the early stages of ChatGPT's release, the study adds a crucial layer of understanding to the ongoing discourse on AI's societal implications [6].

## Literature Review

### Sentiment Analysis in Social Media

The analysis of public discourse on emerging technologies through sentiment analysis has become increasingly relevant as digital platforms amplify societal voices. Studies demonstrate that social media serves as a dynamic source for examining public sentiment, offering real-time insights into societal reactions and emotional undercurrents. For instance, Research [9] utilized sentiment analysis during the COVID-19 pandemic to capture public attitudes toward reopening strategies, showcasing the value of big data in understanding rapid societal changes [10]. Similarly, Research [11] highlighted social media's role in gauging emotional responses to natural disasters, such as Typhoon Haiyan, illustrating its utility in capturing public perceptions during crises [11]. These studies underline the potential of sentiment analysis to reveal patterns in public discourse, particularly in contexts where traditional surveys fall short.

In the realm of artificial intelligence, sentiment analysis has been applied to assess societal attitudes toward AI-driven tools like ChatGPT. Küçük explored ChatGPT's efficacy in sentiment classification tasks, demonstrating its ability to accurately detect sentiment and stance in social media discussions [12]. This research underscores the importance of leveraging advanced AI models to enhance sentiment analysis techniques, particularly when evaluating public discourse on technological advancements. Additionally, research [13] examined public opinions on dockless bike-sharing programs through machine learning-based sentiment analysis, emphasizing the advantages of integrating social media data to complement traditional research methods [13]. These approaches not only mitigate biases inherent in conventional surveys but also enable the

extraction of unfiltered, spontaneous public opinions.

The landscape of sentiment analysis and its applications has been explored extensively across various domains, offering valuable methodologies and insights that inform this study. For instance, sentiment analysis on Indonesian Twitter data has highlighted the efficacy of uncertainty sampling in refining classification models, particularly in dynamic social media contexts [14], [15]. In parallel, the effectiveness of Support Vector Machines (SVM) combined with TF-IDF techniques has been demonstrated in evaluating public sentiment toward electric vehicle incentives, underscoring the utility of advanced machine learning techniques [16], [17]. Studies analyzing Bitcoin-related tweets have further showcased how TF-IDF vectorization and clustering methodologies can uncover sentiment trends, providing a framework for understanding public reactions to emerging technologies [18], [19]. On a broader scale, research into Twitter conversations about the metaverse has demonstrated how discourse analysis on social media reveals dynamic trends and public sentiment shifts, which aligns closely with the objectives of this study [20], [21]. Additionally, insights from predictive modeling using Random Forest and Logistic Regression have highlighted the importance of algorithm selection in sentiment analysis, offering practical guidelines for optimizing analytical outcomes [22], [23]. These studies collectively contribute a rich foundation for exploring public sentiment and emotional dynamics within the context of ChatGPT.

### **Emotion Detection in Text**

Emotion detection in text is a powerful tool for understanding the public's complex and often volatile reactions to emerging technologies like artificial intelligence (AI). As AI increasingly influences various sectors—ranging from healthcare to education—grasping the emotional tone of public discourse becomes critical. Emotions such as excitement, fear, and skepticism are not just peripheral to the conversation; they shape how society interacts with, accepts, or resists these technologies. By detecting and analyzing these emotions, stakeholders—including developers, policymakers, and business leaders—can better understand public sentiment, which directly impacts how AI technologies are adopted and regulated. Public reactions to AI, especially in forums like social media, reveal the underlying fears and hopes that frame technological acceptance, making emotion detection an essential component of sentiment analysis [24].

Emotions, particularly fear and skepticism, often dominate discussions surrounding AI. These sentiments are frequently linked to concerns about job displacement, privacy erosion, and ethical dilemmas that arise from automation. For example, research [24] highlight how fears of unemployment and a loss of human agency in decision-making can fuel skepticism toward AI, even in the face of its potential benefits. Such emotional responses have significant implications for the development and deployment of AI systems. Fear, while often based on real or perceived risks, can create barriers to acceptance, while excitement, which is tied to optimism about AI's transformative power, can drive innovation and investment. Identifying and interpreting these emotional cues in online discussions, such as those on social media, offers valuable insights into the broader societal discourse on AI. This analysis can inform more nuanced policies and strategies that address public concerns while fostering enthusiasm for AI's potential [2].

Moreover, the importance of detecting emotion extends beyond merely understanding public opinion—it enables stakeholders to anticipate and manage

the emotional dynamics that influence AI's societal impact. When public discourse reveals strong emotions like fear or excitement, it signals the need for responsive measures, such as transparent communication or ethical considerations in AI design. As [2] argue, addressing public concerns in a proactive manner can pave the way for smoother integration of AI technologies into daily life. Emotion detection, therefore, not only uncovers the emotional undercurrents in AI discussions but also helps guide the development of AI systems that align more closely with societal values and expectations.

### **VADER Sentiment Analysis**

VADER (Valence Aware Dictionary and sEntiment Reasoner) is a highly specialized sentiment analysis tool designed to assess sentiments expressed in social media text, where language often defies the conventions of formal communication. Developed by Hutto and Gilbert in 2014, VADER stands out due to its unique lexicon-and-rule-based methodology, enabling it to capture the subtleties of social media discourse. Unlike traditional sentiment analysis methods that may struggle with informal, abbreviated, or emotionally charged language, VADER excels in these areas, making it particularly suited for analyzing short, rapid-fire posts on platforms like Twitter, Reddit, and Facebook [25]. By focusing on the emotional tone conveyed through both words and context, VADER offers a nuanced interpretation of user-generated content, providing a comprehensive assessment of sentiment in the digital age.

One of the central features of VADER is its lexicon-based approach, which relies on a predefined dictionary of words and phrases, each linked to a sentiment score. These words and phrases are assigned values that reflect their emotional valence—positive, negative, or neutral. What sets VADER apart is its ability to incorporate not only common sentiment-laden terms but also context-specific elements, such as emojis, punctuation, and capitalization, that are ubiquitous in social media communication [25]. This allows VADER to account for the intensity of sentiment, giving higher scores to emphatic expressions and moderating scores for subtle or neutral language. Furthermore, VADER integrates syntactic rules that adjust sentiment scores based on the context in which words appear, ensuring that sarcastic or contradictory statements are handled appropriately [26]. This combination of lexicon and rules makes VADER an exceptionally robust tool for parsing the rich emotional content that characterizes online conversations.

Another defining aspect of VADER is its ability to handle the challenges posed by informal language, often seen in social media platforms. Unlike many other sentiment analysis tools, VADER performs remarkably well when confronted with non-standard language features, such as emoticons, hashtags, and slang [25]. This is particularly crucial in the context of discussions surrounding emerging technologies like AI, where public sentiment is often mixed and expressed in highly varied forms. Whether users are expressing excitement, skepticism, or confusion, VADER's sensitivity to these emotional nuances enables it to provide a more accurate representation of the public's collective sentiment, making it an invaluable tool for sentiment and emotion analysis in the rapidly evolving digital landscape.

### **Existing Research on ChatGPT Sentiment**

Public reactions to AI tools such as ChatGPT have become a central focus in research, particularly in the realms of technology adoption, ethical concerns, and broader societal implications. As AI technologies continue to evolve,



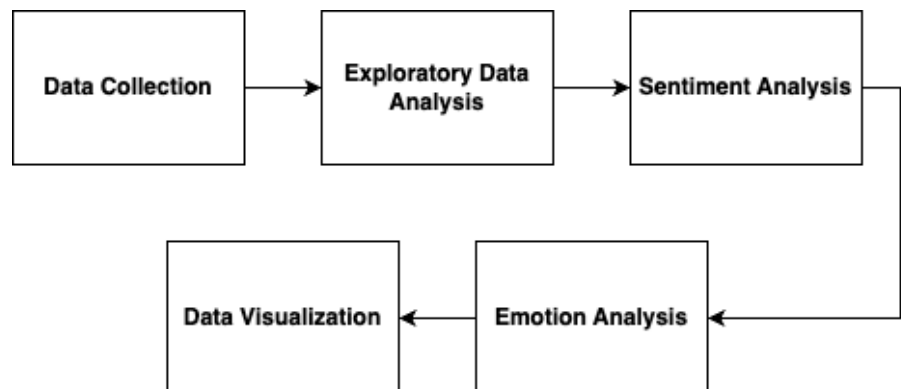
understanding the public's response is essential not only for developers but also for policymakers and businesses. A variety of studies have delved into how people perceive AI, often highlighting the complex interplay of excitement, skepticism, and fear. Researchers have examined public attitudes through surveys, sentiment analysis, and ethnographic studies, shedding light on the factors that influence AI acceptance and its role in shaping societal dynamics [27]. These studies underscore the importance of public sentiment in determining the trajectory of AI technologies, revealing that the conversation surrounding AI is as much about emotional reactions as it is about technical capabilities.

In the context of technology adoption, research consistently shows that perceived usefulness and ease of use significantly shape public sentiment towards tools like ChatGPT. Su (2023) argues that understanding user attitudes is pivotal for the successful integration of AI into society. This is particularly evident in the case of ChatGPT, where users' perceptions of the tool's utility in daily tasks, such as content generation and customer service, directly impact its acceptance. The widespread enthusiasm for ChatGPT among early adopters contrasts with concerns raised by others who question its potential to disrupt traditional industries and displace human workers. This divergence in opinion reflects broader debates about the role of AI in reshaping the workforce and society at large [2]. Such contrasting viewpoints are not only influenced by the perceived utility of the technology but also by the ethical and social implications tied to its use.

Ethical concerns surrounding AI technologies like ChatGPT have become another focal point of public discourse. Research indicates that fears about privacy, data security, and the potential misuse of AI for malicious purposes are significant barriers to AI acceptance [4]. For instance, studies have shown that while many users are eager to embrace the capabilities of AI tools, they remain wary of how their data may be used or misused. The ethical dimension of AI adoption continues to fuel debates on regulation and accountability, with many calling for clearer guidelines to govern the development and deployment of such technologies [28]. These concerns highlight the critical need for responsible AI development that aligns with public interests and ensures transparency in its implementation.

## Method

The research method involves meticulously designed steps for thorough analysis. Figure 1 outlines the comprehensive steps.



**Figure 1 Research Method Flowchart**

## Data Collection

For this study, the dataset consists of tweets discussing ChatGPT, sourced from Kaggle, a platform known for hosting diverse datasets for research and analysis. This dataset captures public discourse from Twitter, a widely utilized social media platform that provides a real-time window into user sentiments, opinions, and emotions regarding ChatGPT. Curated to reflect a wide spectrum of interactions, the dataset includes expressions of excitement, praise, skepticism, and concern. To uphold ethical standards and ensure privacy compliance, the data has been anonymized by removing personally identifiable information, making it suitable for academic and analytical purposes.

The dataset, stored in a CSV file format, includes a variety of relevant columns, such as tweet content, user information (anonymized), timestamps, and metadata associated with each tweet. The data is encoded using ISO-8859-1 to handle any potential encoding issues, especially when dealing with non-UTF-8 characters that might appear in the tweet texts. To improve data quality, any problematic or malformed entries were excluded from the analysis using the 'on\_bad\_lines' parameter in the `pd.read_csv` function. By inspecting the first few rows of the dataset, it is possible to ensure that the collected data aligns with the research objectives, allowing for a thorough analysis of public sentiment towards ChatGPT. This dataset serves as the foundation for subsequent sentiment and emotion analysis, leveraging tools such as VADER to explore the emotional tone of the tweets.

## Exploratory Data Analysis (EDA)

Exploratory Data Analysis (EDA) plays a critical role in understanding the underlying structure and characteristics of the dataset, which is pivotal for any subsequent analysis. The first step in the EDA process involves basic statistical analysis to gain a high-level overview of the dataset. For this research, several key metrics are examined, including word count, tweet length, and tweet volume. Word count, as a simple but powerful measure, offers insights into how much text is typically generated in a tweet, which can provide valuable context for analyzing sentiment intensity. Additionally, tweet length serves as another important feature, as it can reveal patterns in user engagement and expression. By tracking these metrics across the dataset, we can identify any trends or anomalies that might influence the sentiment analysis later in the study.

The dataset was enriched by adding a new column that calculates the word count for each tweet. This is achieved by using the `.str.split()` method to break each tweet into individual words and then applying the `.apply()` function to count the number of words per tweet. Similarly, tweet length was computed by calculating the number of characters in each tweet, providing a clear view of how succinct or elaborate the discourse surrounding ChatGPT is. These basic statistics were visualized using histograms and boxplots, offering a compelling view of tweet distribution across various dimensions. Visual representations such as these allow for the detection of any outliers or skewness in tweet length and word count, which could skew sentiment scores if left unaddressed. For instance, a few excessively long tweets might reflect promotional content or external links, distorting the analysis.

However, raw data from social media often includes noisy elements, such as URLs, user mentions, and special characters, which can interfere with the accuracy of sentiment analysis. Data cleaning thus becomes an essential step in preparing the dataset for further analysis. The presence of URLs, for example, while indicative of the spread of information, carries little semantic value in sentiment analysis and could bias results if not properly handled. Similarly, user mentions (e.g., @username) are context-specific and may not contribute to the overall sentiment but could impact the tone if left in the dataset. Special characters like punctuation marks or emojis also require careful handling, as they could be misinterpreted by sentiment analysis models.

To address these issues, a series of preprocessing steps were executed to remove these elements from the dataset. Using regular expressions (regex), URLs were removed by searching for common patterns such as “http://” and “https://”. Similarly, mentions and hashtags were excluded using regex patterns that target the “@” and “#” symbols. Emojis, often used to convey emotions but challenging for certain sentiment analysis tools, were either removed or replaced with neutral placeholders to prevent them from skewing the analysis. Once the data was cleaned, the refined dataset was ready for deeper sentiment analysis, with the primary goal of uncovering public reactions to ChatGPT and understanding how emotional tone varies across different types of discourse. These foundational steps in the EDA process not only enhance the quality of the data but also ensure that the results are grounded in a robust and meaningful analysis.

### **Sentiment and Emotion Analysis**

Sentiment and emotion analysis represent a cornerstone of understanding public perception, particularly when examining emerging technologies such as ChatGPT. For this research, the VADER (Valence Aware Dictionary and sEntiment Reasoner) sentiment analysis algorithm is applied to identify and measure the emotional tone of the tweets in the dataset. VADER is well-suited for this task, as it excels in analyzing social media text, where the language is often informal, filled with emoticons, and rich with nuances. The algorithm assigns a sentiment score to each tweet based on predefined lexicons and grammatical heuristics, classifying the sentiment as positive, negative, or neutral while also providing a score for the intensity of the sentiment [25]. This score allows for a fine-grained understanding of the emotional landscape surrounding ChatGPT discussions.

Before applying VADER to the dataset, several preprocessing steps are carried out to ensure the accuracy and consistency of the sentiment analysis. Tokenization, the process of splitting text into individual words or tokens, is one of the first steps in preparing the text for analysis. This is followed by converting all text to lowercase, a necessary step to maintain uniformity, as VADER is case-sensitive and treats words like “AI” and “ai” as different. Moreover, stopword removal is employed to eliminate common words (e.g., “the”, “is”, “and”) that, while frequent, do not contribute to the sentiment or emotional tone of the tweet. These preprocessing steps are critical, as they remove unnecessary noise and enhance the precision of the sentiment scores, ensuring that only the most meaningful linguistic elements are analyzed [29].

Once the text is cleaned and preprocessed, the VADER SentimentIntensityAnalyzer is applied to compute sentiment scores for each



tweet. This tool provides four distinct scores: positive, neutral, negative, and a composite score that summarizes the overall sentiment expressed. The composite score, ranging from -1 (most negative) to +1 (most positive), enables a comprehensive assessment of public sentiment. For example, tweets expressing excitement or praise for ChatGPT would yield a higher positive score, while those reflecting skepticism or concerns about AI ethics would lean towards negative scores [26]. The intensity of the sentiment, which is also captured, allows for the identification of tweets that carry strong emotional responses, which are often the most impactful in shaping public discourse.

To visualize the distribution of sentiments, histograms and bar charts are used, providing an intuitive understanding of how public sentiment toward ChatGPT is distributed. By analyzing the sentiment scores, trends and patterns in public reactions can be identified, highlighting key emotional reactions such as excitement, fear, or skepticism. For instance, spikes in negative sentiment might correlate with discussions about AI ethics or concerns over privacy, while positive sentiment might reflect excitement about the potential of ChatGPT in transforming communication and productivity. This analysis not only aids in quantifying public opinion but also offers insights into the broader societal conversation surrounding AI, helping to uncover underlying themes that shape the trajectory of AI technologies [2].

### **Data Visualization**

Data visualization serves as a powerful tool in sentiment and emotion analysis, transforming complex quantitative results into clear, accessible insights. In this study, several types of visual representations are utilized to illustrate the distribution of sentiment across the dataset and to track emotional trends over time. One of the first visualizations generated is a bar chart depicting the frequency of positive, negative, and neutral tweets. This chart provides an immediate overview of the general sentiment surrounding ChatGPT, allowing researchers to discern at a glance whether the public's reactions tend to be more positive, negative, or neutral. Such visualizations are essential for conveying the overall mood of a dataset in a digestible format, reinforcing the impact of emerging AI technologies on public discourse.

To deepen the analysis, time-based sentiment trends are also explored. By aggregating the sentiment scores over time, the study tracks how public opinion fluctuates throughout specific periods, such as major updates to ChatGPT or prominent news stories about AI ethics. These temporal visualizations, often represented as line charts, allow for the identification of sentiment spikes, shifts, or periods of stability. For example, a sharp rise in negative sentiment might correlate with a particular controversy or ethical debate related to ChatGPT. This method of sentiment tracking is crucial for understanding the dynamic relationship between AI tools and public opinion, illustrating how sentiment is influenced not just by the technology itself but also by the ongoing socio-political conversation surrounding it.

In addition to sentiment-based charts, emotion visualization is achieved through word clouds and pie charts. Word clouds provide a rich, visual representation of the most frequently mentioned words within tweets expressing strong emotions. For instance, a word cloud generated from tweets containing predominantly positive sentiments might highlight words such as "impressed," "amazing," or "innovative," while negative tweets might bring words like

“concern,” “privacy,” or “scary” to the forefront. This tool helps to contextualize the sentiment by showing the emotional vocabulary that shapes public opinion. Furthermore, pie charts are employed to depict the distribution of specific emotions, such as joy, fear, and excitement, within the dataset. These visualizations offer an emotional snapshot of the public’s reaction to ChatGPT, allowing for nuanced insights into the underlying feelings driving the discourse.

The integration of these visual tools enables a comprehensive understanding of the emotional landscape surrounding ChatGPT. By combining sentiment analysis with visual representation, the study not only quantifies public opinion but also provides a more tangible, intuitive way to grasp the complexities of public reaction. These visualizations help bridge the gap between raw data and actionable insights, offering both immediate clarity and deeper, more nuanced understanding. This approach underscores the critical role of data visualization in analyzing the emotional and sentimental dynamics of AI discourse, facilitating communication between researchers and the broader public while ensuring that findings are accessible, interpretable, and impactful.

## Result and Discussion

### Sentiment Analysis Results

The sentiment analysis of tweets discussing ChatGPT reveals a diverse emotional landscape, reflecting public reactions to the technology. The dataset demonstrates a clear division among sentiment categories: 47.9% of tweets were classified as positive, 35.4% as neutral, and 16.8% as negative. This distribution indicates a predominantly favorable perception of ChatGPT among Twitter users, with a significant portion of users engaging with the tool in an exploratory or indifferent manner. The minority of negative tweets highlights concerns or criticisms that merit further investigation. Such a distribution underscores the complexity of public discourse surrounding emerging technologies, where enthusiasm often coexists with apprehension.

The sentiment distribution was visualized using a bar chart ([Figure 2](#)), offering a clear representation of the frequency of positive, neutral, and negative sentiments. The bar chart reveals a dominant cluster of positive tweets, followed by neutral and then negative sentiments, suggesting a generally optimistic outlook toward ChatGPT’s capabilities and implications. Neutral tweets, which likely include informational or descriptive content, also play a critical role in reflecting the widespread curiosity about AI. This visual analysis facilitates the identification of sentiment trends, allowing researchers to pinpoint areas where public perception is either highly supportive or critically skeptical.

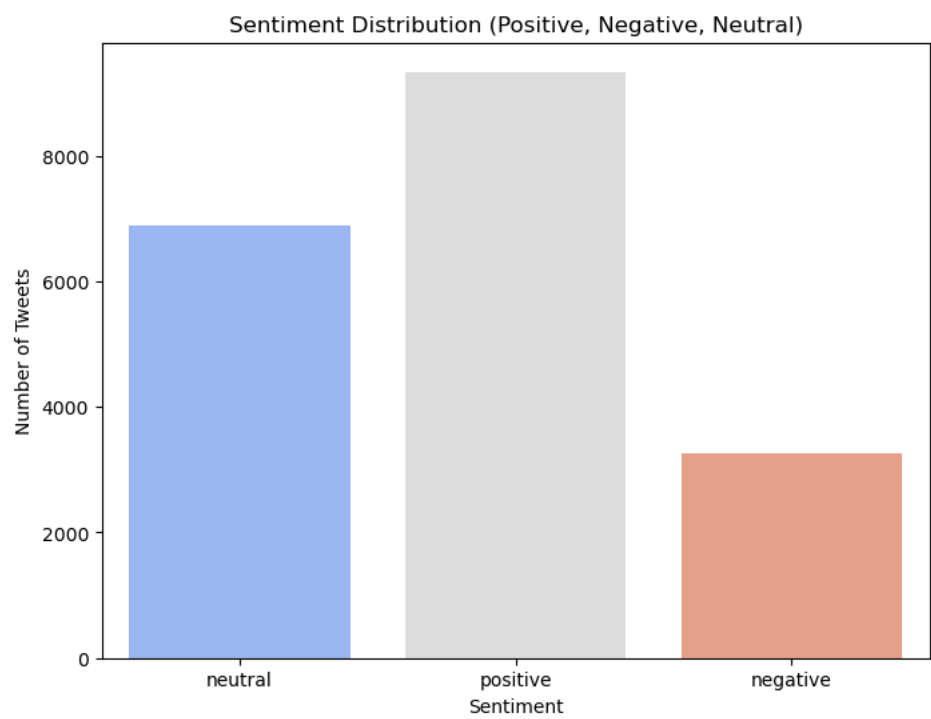
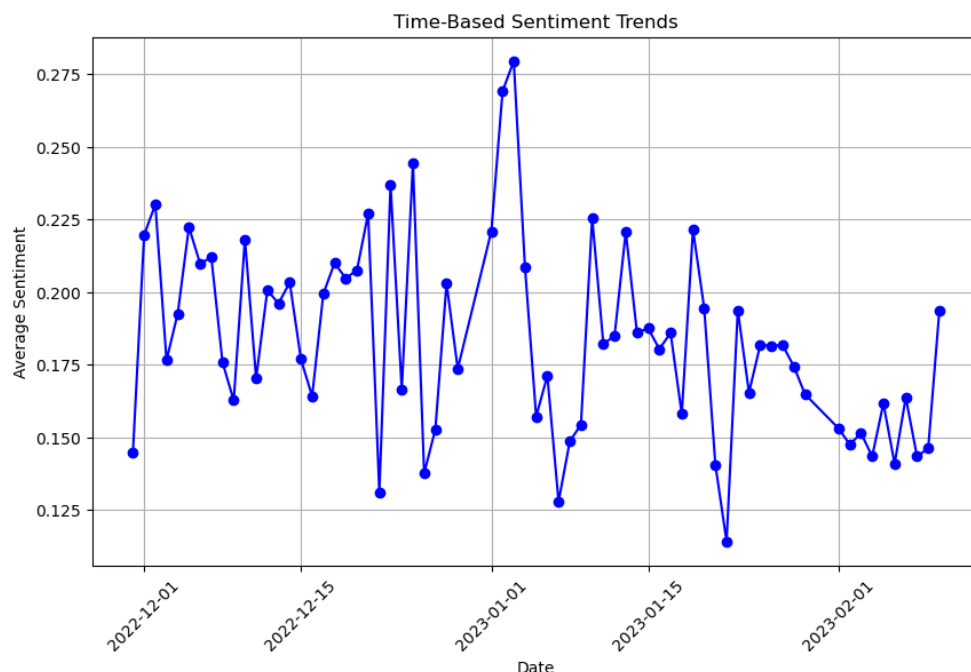


Figure 2 Sentiment Distribution

To explore temporal patterns, a time-based sentiment trend analysis was conducted (Figure 3), using daily average sentiment scores to track fluctuations over the study period. The resulting line graph revealed spikes in sentiment coinciding with significant events, such as updates to ChatGPT or public discussions on AI ethics and societal impact. For instance, a noticeable rise in positive sentiment occurred shortly after the announcement of a major feature upgrade, demonstrating the public’s enthusiasm for technological progress. Conversely, dips in sentiment corresponded to debates over privacy concerns and AI’s potential risks, illustrating how specific topics can influence public attitudes. These findings emphasize the dynamic nature of public opinion, shaped by both technological advancements and societal narratives.

**Figure 3 Time-Based Sentiment Trends**

### Emotional Tone and Trends

Emotion analysis further enriched the sentiment results by categorizing tweets into emotional themes such as joy, fear, and excitement. A pie chart (Figure 4) revealed that 47.9% of tweets expressed joy, correlating strongly with positive sentiment. Fear, representing 16.8%, was predominantly linked to negative sentiment, reflecting concerns about AI's ethical and societal implications. Excitement, encompassing 35.4%, aligned with neutral sentiment, indicating a sense of curiosity and anticipation about ChatGPT's potential applications. Additionally, a word cloud visualization highlighted prominent terms associated with each sentiment, providing qualitative insights into the public's language and emotional tone. Together, these visual and analytical tools offer a nuanced understanding of the emotional drivers behind the public's engagement with ChatGPT.

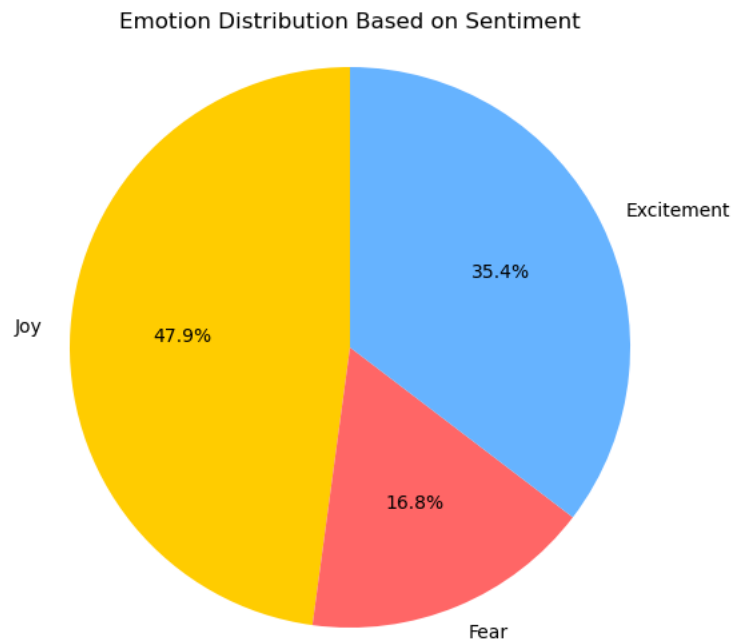


Figure 4 Emotion Distribution Based on Sentiment

The analysis of emotional tones in tweets discussing ChatGPT reveals a multifaceted public reaction, highlighting the diverse range of emotions elicited by the technology. Among the most prominent emotional tones identified were joy, fear, and excitement, each reflecting distinct dimensions of public engagement with ChatGPT. Joy emerged as the dominant tone, evident in the high proportion of tweets expressing positive emotions such as amazement, inspiration, and satisfaction with the tool’s capabilities. This emotional tone underscores the public’s enthusiasm for ChatGPT’s potential to revolutionize tasks such as content creation, problem-solving, and communication, particularly in professional and educational settings.

Fear, though less prevalent, provided critical insights into public apprehensions about ChatGPT. This emotional tone often centered on ethical concerns, job displacement fears, and anxieties about privacy and data misuse. The presence of fear-driven tweets highlights the undercurrent of skepticism that accompanies the adoption of transformative technologies like AI. For instance, tweets expressing fear frequently referenced scenarios where AI might replace human roles or exacerbate existing inequalities. These findings resonate with existing literature emphasizing the role of fear in shaping public discourse around disruptive technologies. Such insights are vital for understanding the challenges faced by developers and policymakers in addressing these concerns to foster broader acceptance of AI technologies.

To provide a qualitative dimension to these findings, a word cloud visualization was generated (Figure 5), capturing the most frequently used emotional words within the dataset. The word cloud visualization provides a compelling summary of the most commonly occurring words in tweets discussing ChatGPT. Dominating the cloud is the term “ChatGPT,” highlighting its central role in the discourse. Surrounding it are key terms like “AI,” “Google,” and “tool,” which emphasize ChatGPT’s position within the broader context of artificial intelligence and its functionality as a practical tool. Notable words such as





public views ChatGPT as a transformative tool with the potential to enhance creativity, efficiency, and productivity. This aligns with the growing acceptance of AI technologies in domains such as education, content creation, and customer service, where ChatGPT's capabilities are often celebrated as groundbreaking. However, the presence of fear-driven sentiment, though less frequent, underscores the persistence of critical questions about AI ethics, data privacy, and potential job displacement. These concerns indicate that while the public is intrigued by ChatGPT's promise, deeper engagement is necessary to address underlying anxieties and foster trust in the technology.

When compared to findings from similar studies on AI-related discourse, the public's reaction to ChatGPT appears consistent with broader trends in the adoption of emerging technologies. For instance, studies examining public sentiment towards AI in healthcare and finance have also identified a dichotomy between optimism for innovation and fear of ethical challenges. The emotional responses captured in this study, particularly the emphasis on joy and fear, mirror these patterns, suggesting that public perceptions of AI are often shaped by a mix of hope for societal progress and caution against potential risks. This duality highlights the complexity of public engagement with AI, requiring developers and policymakers to strike a balance between promoting the benefits of these technologies and addressing the challenges they pose.

### **Limitations**

Despite the valuable insights gained, this study acknowledges several limitations that may influence the interpretation of the results. One significant constraint lies in the reliance on Twitter as the sole source of data. While Twitter provides a rich repository of user-generated content, its user base is not fully representative of the broader population, potentially introducing bias into the findings. For example, opinions expressed on Twitter often skew toward younger, tech-savvy demographics, potentially overlooking perspectives from older or less digitally literate populations. Additionally, the limitations of the VADER sentiment analysis tool should be considered. While VADER is effective in identifying general sentiment and emotional tone, it struggles to detect sarcasm, irony, and nuanced emotions that are frequently embedded in social media language. As a result, the sentiment scores may occasionally misclassify tweets, particularly those employing complex linguistic structures.

### **Implications**

The findings of this study hold significant implications for AI development, digital society, and the ethical considerations surrounding the rollout of new technologies. For AI developers, the insights into public sentiment and emotional responses emphasize the importance of designing technologies that are not only innovative but also aligned with societal values and expectations. Addressing concerns about data privacy, ethical transparency, and potential job displacement can enhance public trust and adoption rates. For policymakers, these findings underscore the need to create regulatory frameworks that balance technological advancement with protections for societal well-being. Furthermore, the study highlights the critical role of effective communication strategies in shaping public discourse, suggesting that stakeholders should engage more proactively with the public to dispel misconceptions and emphasize the potential benefits of AI. Ultimately, this study contributes to the broader conversation about the integration of AI technologies into digital society,

advocating for a more thoughtful and inclusive approach to their development and deployment.

## Conclusion

The analysis of public discourse on ChatGPT during its initial launch period has revealed a dynamic interplay between enthusiasm and concern, encapsulated within the sentiments and emotions expressed by users. Positive sentiment dominated the landscape, reflecting widespread fascination and optimism regarding the technology's potential to transform creative, professional, and educational spheres. Words associated with joy, such as "amazing" and "exciting," underscored this enthusiasm. However, as public engagement deepened, concerns over AI ethics, particularly regarding privacy, job displacement, and misuse, began to surface more prominently. These contrasting emotions reflect a duality that is emblematic of public interaction with emerging technologies, highlighting the tension between innovation and its societal implications.

This study contributes to the growing body of literature on AI technologies by providing an empirical examination of public reactions to ChatGPT during its critical early adoption phase. By analyzing sentiments and emotions expressed on social media, the study offers a nuanced understanding of how the public perceives and interacts with AI-driven tools. This research not only sheds light on the factors driving positive sentiment, such as utility and accessibility, but also highlights the underlying concerns that could hinder broader acceptance. These findings enrich the discourse on AI and digital society by bridging quantitative sentiment analysis with qualitative emotional insights, thereby advancing methodologies for studying public opinion in the context of technological innovation.

While this study has illuminated key trends in sentiment and emotional tone, several areas warrant further exploration. Future research could delve deeper into the granular nuances of emotions, examining specific categories such as trust, anxiety, or skepticism, which are often pivotal in shaping public opinion. Additionally, comparative analyses across multiple social media platforms, such as Reddit, Instagram, or LinkedIn, could provide a broader understanding of how different communities perceive and discuss AI technologies. Expanding the scope to include longitudinal studies might also reveal how public sentiment evolves over time in response to updates, controversies, or advancements in ChatGPT and similar tools. Such investigations would deepen our understanding of the societal impact of AI and refine strategies for fostering public trust.

For AI developers, the findings of this study underscore the importance of proactive public engagement strategies to address both enthusiasm and apprehension effectively. Emphasizing transparency in data usage, creating educational initiatives to demystify AI functionalities, and fostering open dialogues about ethical considerations can significantly enhance public trust. Developers are encouraged to monitor sentiment trends continuously, using insights from emotion analysis to tailor communication and outreach efforts. Policymakers should collaborate with developers to establish frameworks that safeguard societal interests while promoting innovation. Together, these measures can bridge the gap between technological advancement and public acceptance, ensuring that tools like ChatGPT are embraced as assets rather

than threats to digital society.

## Declarations

### Author Contributions

Conceptualization: I.C.; Methodology: I.M.M.E.; Software: E.G.; Validation: I.M.M.E.; Formal Analysis: A.G.; Investigation: I.M.M.E.; Resources: I.C.; Data Curation: I.M.M.E.; Writing Original Draft Preparation: K.L.; Writing Review and Editing: I.C.; Visualization: I.M.M.E.; All authors have read and agreed to the published version of the manuscript.

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The data presented in this study are available on request from the corresponding author.

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### Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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