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Tides of emotion: the impact of the COVID-19 policy on public sentiment in Shanghai during the city closure

By

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Abstract

This study analyzes the impact of six epidemic prevention policies implemented in Shanghai during the COVID-19 outbreak on residents' emotions by analyzing approximately 270,000 posts on Sina Weibo, using the Plutchik Emotion Wheel model and the BERT model. The research covers emotions such as "disgust," "sadness," "anticipation," revealing the dynamic relationship between policies and changes in emotions.Research findings indicate that negative emotions such as disgust and sadness increase significantly during adverse events like the initiation of lockdowns; conversely, positive emotions like trust see a certain degree of increase after favorable events such as the resumption of work. Additionally, the study discovered a substantial rise in the proportion of disgust following the work resumed announcement. This increase stems from the people of Shanghai's dissatisfaction with the sudden lifting of the lockdown leading to potential health risks, discontent with the government's mismanagement during the lockdown, and concerns over their economic repayment capabilities and employment. This paper aims to provide theoretical support for the Chinese government in addressing the next public health crisis, based on the findings of this study.

Keywords: COVID-19 pandemic; emotional analysis; Plutchik's Wheel of Emotions; BERT model; Shanghai lockdown

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1 Introduction

Major emergencies are defined as natural or man-made disasters that suddenly occur and can cause significant harm to society, necessitating the implementation of emergency response measures (Anderson & Gerber, 2018). The COVID-19 pandemic is a prime example of such an emergency. In early 2020, following the report of the first case of COVID-19 in Wuhan, the city quickly went into lockdown, and within months, the pandemic erupted globally, profoundly affecting the socio-economic structure and order of China and the world at large(Zhang et al., 2020). Particularly in Shanghai, one of China's most important economic and social hubs, a series of strict epidemic prevention measures were implemented, including comprehensive lockdowns, travel restrictions, stay-at-home orders, and daily mass nucleic acid testing. While these policies were crucial in curbing the spread of the epidemic, they also had significant impacts on the city's economy, social life, and the psychological health of its citizens, sparking widespread discussions on epidemic management strategies, public policy, and social cohesion.

This study aims to delve into the impact of related epidemic prevention policies and announcements on the emotions of residents during the lockdown period in Shanghai by applying the Plutchik Wheel of Emotions model and the BERT model. Utilizing nearly 270,000 text data from Weibo—a leading social media platform in China—this paper explores the specific effects of policies and announcements on public emotions, intending to provide the government with references for responding to future sudden public health events.

In current domestic and international academic research, due to sensitivity issues, there are few studies that directly explore the relationship between policies and public emotions during Shanghai's COVID-19 lockdown. Moreover, in academic papers studying the relationship between China's COVID-19 epidemic and public emotions, most research adopts the method of constructing a proprietary sentiment dictionary to calculate emotional scores for each post through training machine learning models. However, this study adopts an innovative approach based on the established Plutchik's Wheel of Emotions model, combining manual emotion categorization with a BERT model optimized for Chinese to classify emotions. This method focuses on analyzing the changes in the proportion of each emotion category relative to the total emotions, rather than the average score of individual emotions. Furthermore, unlike previous studies that had small sample sizes and limited data sources, this study extensively collected nearly 270,000 posts from Shanghai users on the Sina Weibo platform, from before to after the outbreak began. This significantly expands the coverage and depth of the data sample, providing valuable data support for a deeper understanding of the actual impact of policy changes on public emotions.

The research focuses on: (1) The impact of policies and announcements on the emotions of the people in Shanghai during the lockdown period; (2) The trend of changes in residents' emotions. Through a comprehensive analysis of the lockdown period in Shanghai, this paper not only offers insights into urban management in the context of the COVID-19 pandemic but also provides a strategic framework and policy recommendations for future potential public health crises.

2 Background

This paper has selected six extremely important epidemic-related policies or announcements that have driven changes during the lockdown period. They may represent the beginning, the end, the climax, or a turning point. Specifically, they are:

- **March 1, 2022: "First Case Reported" (Liu and Tu 2022)**
  Shanghai reported its first COVID-19 case of 2022, marking the start of a new round of epidemic challenges for the city. The confirmation of this case garnered significant attention from public health departments, indicating that stricter epidemic prevention measures might be necessary to prevent further spread of the virus.

- **March 27, 2022: "Begin Lockdowns" (Xiong, McCarthy, and Khalil 2022)**
  In response to the rapid increase in case numbers, Shanghai initiated lockdown measures on March 27. These measures included restricting people's movement, closing non-essential businesses, and postponing the opening of schools and workplaces. The purpose of the lockdown was to slow the spread of the virus and buy valuable preparation time for the healthcare system.

- **April 5, 2022: "Measures Launched" (NBC NEWS, 2022)**
  The full lockdown in Shanghai began on April 5, 2022. The initial plan was to conduct large-scale nucleic acid testing in two phases:

  - The first phase: targeted the Pudong New Area, implemented from March 28 to April 1, 2022.
  - The second phase: targeted the Puxi area, starting from April 1.

  However, due to the rapid spread of the COVID-19 Omicron variant, this phased plan quickly evolved into a more prolonged citywide lockdown. Starting April 5, Shanghai entered a stricter lockdown state, with nearly the entire city required to stay at home, a condition that lasted for several weeks.

- **April 29, 2022: "Zero Case Growth" (Reuters, 2022)**
  On April 29, Shanghai reported zero new daily cases for the first time since the implementation of lockdown measures, marking a significant milestone in the effectiveness of the epidemic prevention efforts. This achievement brought hope to the city, demonstrating the effectiveness of the lockdown and epidemic prevention measures.

- **June 1, 2022: "Work Resumed" (Xu and Wang 2022)**
  As the epidemic was effectively controlled, Shanghai began to orderly resume work and production on June 1. This move aimed to gradually restore normal economic activities and social order while continuing to implement necessary epidemic prevention measures to prevent a rebound of the epidemic.

- **June 25, 2022: "Victory Declared" (Bloomberg 2022)**
  After months of arduous efforts, Shanghai declared victory over this round of the COVID-19 epidemic on June 25. This signified that the city could gradually return to normal daily life and economic activities while ensuring the health of its residents.

3 Literature Review

3.1Plutchik's Emotion Model in Sentiment Analysis

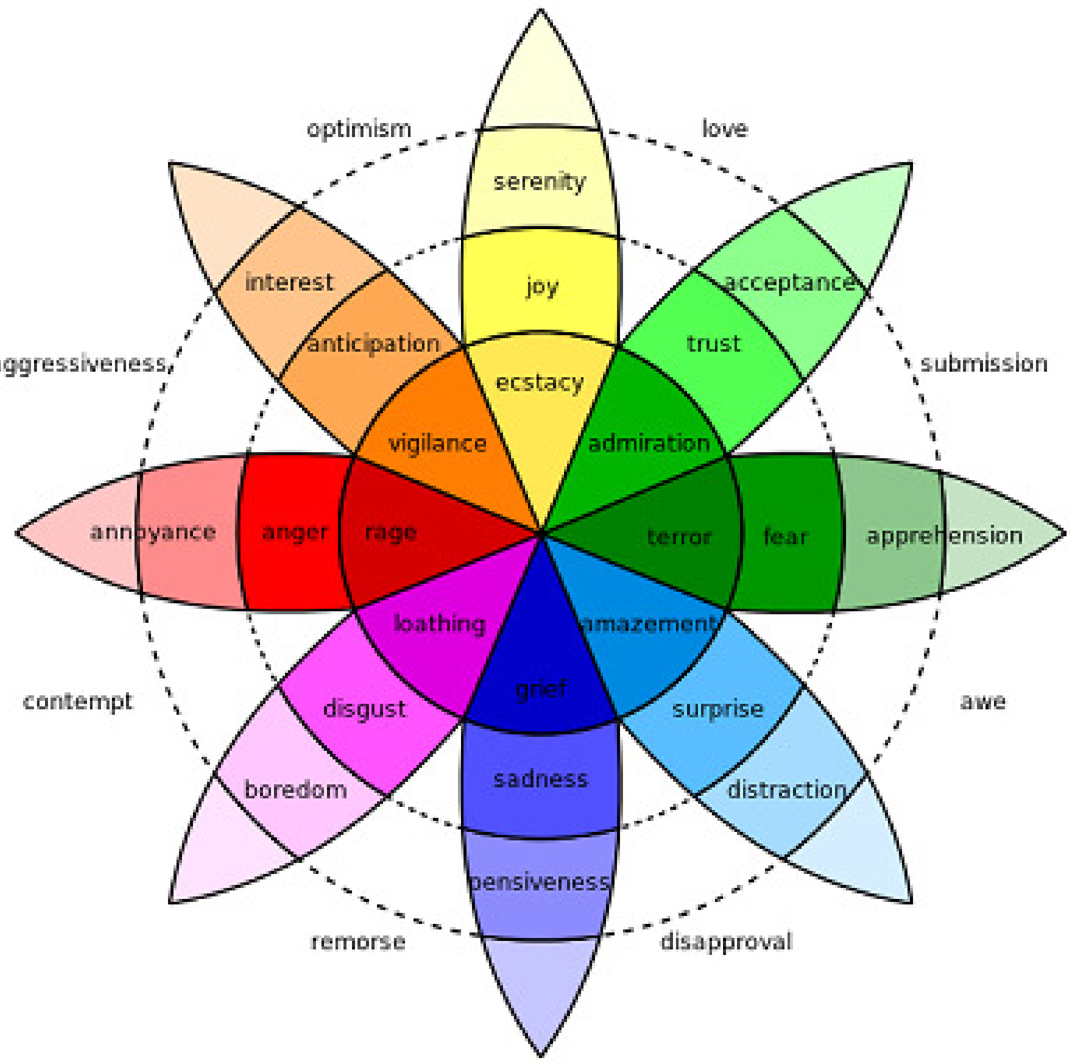

Figure 1: P
lutchik's Wheel of Emotions

The Wheel of Emotions, conceived by Robert Plutchik, presents a comprehensive framework for understanding and classifying human emotions. This model identifies eight primary emotions: joy, sadness, anger, fear, trust, disgust, surprise, and anticipation. These emotions are organized into four opposing pairs, embodying the complex interplay of human feelings. Plutchik's model further illustrates the capacity for these primary emotions to blend and vary in intensity, thus enabling the construction of a broader spectrum of emotional experiences. For example, emotions such as love emerge from the combination of joy and trust, while jealousy incorporates elements of joy, trust, and anger(Abbasi Mohsin & Beltiukov, 2019).

The significance of Plutchik's Wheel of Emotions extends beyond theoretical psychology into the realm of computational sentiment analysis. This model offers a structured approach to emotion identification and analysis in text, presenting a challenge due to the inherently subjective nature of emotional expression. Early efforts to establish standards in emotion analysis from text have been pioneered by researchers (Parrott, 2001; Robert, 1980; Schroder et al., 2011). They aimed to define a core set of emotions that serve as building blocks for more complex emotional constructs.

In the contemporary landscape of sentiment analysis, the application of Plutchik's model has seen diverse implementations. Abbasi and Beltiukov (2021) utilized the model to weigh emotions in internet communication, demonstrating the model's efficacy in capturing emotional intensity variations. Similarly, Vaishali Ganganwara and colleagues (2021) applied the model to analyze sentiments within legal emails, categorizing emotions into eight classes and reporting high accuracy using Recurrent Neural Networks. Mondal and Gokhale (2021) explored emotion detection in tweets, mapping emotions to binary classification problems in line with Plutchik's wheel, with notable success in accuracy using machine learning classifiers.

A particularly interesting application was conducted by Treceñe (2019), who employed a Plutchik-based sentiment analysis on students' learning diaries to investigate emotions related to gender issues. This study underscores the utility of sentiment analysis in educational research, revealing the emotional dynamics influenced by teaching strategies and classroom discussions.

In summary, Plutchik's Wheel of Emotions serves as a vital reference point for developing sentiment analysis models and methods. Its comprehensive coverage of basic to complex emotions facilitates a nuanced understanding of emotional expressions in text. This literature review highlights the model's versatility across different research contexts, underscoring its enduring relevance in the field of sentiment analysis.

Plutchik's Wheel of Emotions has been praised for its expansion of the dimensions of emotions, providing a more comprehensive view of the complexity of human emotions by including more emotions and combinations of emotions. Not only does this model serve as an important tool in education and psychotherapy to help individuals identify and express their emotional states to better manage emotional health, but it also facilitates interdisciplinary applications that link emotions to other fields such as art and design, allowing emotional understanding to be applied and explored in a wider range of fields (Petrauskas, 2022). However, there are some limitations to this model. It may oversimplify the complexity of emotions and make it difficult to capture the nuances of individual emotional experiences; furthermore, differences in the expression and understanding of emotions in different cultures may affect the global applicability and effectiveness of the model; and there are difficulties in translating theoretical knowledge into practical applications.

3.2 Advancements in Sentiment Analysis Technologies

The utilization of sentiment analysis, a pivotal technique for discerning and categorizing emotions within text, has significantly advanced across various domains, notably within social media contexts during health crises such as pandemics. This approach is bifurcated into two primary categories: text sentiment recognition and the analysis of emotions conveyed through images and audio(Nandwani and Verma, 2021) .Text sentiment analysis, in particular, adopts three main methodologies: lexicon-based, traditional machine learning, and deep learning approaches, with the latter emerging as the predominant method in recent times. Deep learning elevates sentiment analysis by abstracting it to a feature level, thereby minimizing the need for manual feature extraction and effectively modeling the relational dynamics between words. This innovation in machine learning, initially introduced by Hinton, Osindero, and Teh (2006), has found applications in data mining, machine translation, natural language processing (NLP), and multimedia learning, marking a significant shift from traditional analysis methods to deep learning paradigms (Devlin et al., 2018).

The advent of Google's BERT (Bidirectional Encoder Representations from Transformers) model towards the end of 2018 marked a milestone in NLP tasks, outperforming nearly all existing deep learning models. Its unique capabilities led researchers to apply BERT to various fields, including sentiment analysis. Studies integrating BERT with convolutional neural networks and bidirectional long short-term memory networks have demonstrated its effectiveness in mining customer sentiments from food reviews, contributing significantly to text sentiment mining research (Yong et al., 2022; Tanana et al., 2021; Cui et al., 2021). For instance, Wang, Lu, Chow, and Zhu (2020) employed the unsupervised BERT model for sentiment classification of nearly one million COVID-19 related Weibo posts, underscoring BERT's precision in categorizing sentiments into positive, neutral, and negative expressions. This underscores BERT's potential in gleaning valuable insights from social media data, particularly in the public health domain.

In parallel, the exploration of social media sentiment during pandemics such as H1N1 and COVID-19 has illuminated public attitudes and responses. Early investigations by Chew and Eysenback (2010) have paved the way for extensive research in this domain, with subsequent studies by Abd-Alrazaq et al. (2020), Zhao et al. (2020), and Samuel et al. (2020) expanding our understanding of public sentiment regarding the COVID-19 pandemic. These studies have shed light on themes ranging from the virus's origin to societal impacts, including the influence of misinformation and bots on public opinion (Ferrara, 2020; Kouzy et al., 2020; Singh et al., 2020). The importance of positive government messaging on social media platforms for enhancing public engagement was also highlighted (Chen et al., 2020; Cinelli et al., 2020).

Further, Che et al. (2021) conducted an insightful study analyzing the impact of daily new COVID-19 case videos posted on TikTok by public health agencies during the 2022 Shanghai lockdown. Using the ERNIE pre-trained model for sentiment classification and semantic network analysis, they mapped public sentiment and concerns across different stages of the crisis communication model. The study highlighted a range of public reactions, from initial reluctance to cooperate due to the high costs of epidemic measures to eventual fatigue with ongoing case updates as the pandemic normalized. The findings underscore the crucial role of targeted communication strategies in managing public sentiment during health crises, providing valuable insights for government and health agencies to enhance public engagement and compliance.

This literature review encapsulates the evolution of sentiment analysis methodologies and their application in monitoring public sentiment during pandemics, underscoring the potential of advanced models like BERT in enhancing our understanding of public emotions through social media data. The synthesis of these studies offers invaluable insights into the dynamics of public sentiment in times of global health crises, providing a foundation for future research and policy evaluation.

In contrast to the study by Che et al. (2024), the study used a manual sentiment classification approach with the Plutchik sentiment wheel model, performed by a graduate student familiar with urban lockdown scenarios to obtain an initial training dataset, followed by retraining an already well-established Chinese bert model with this training set, thus enhancing the depth and reliability of the sentiment analysis during the COVID-19 pandemic. This approach captures a more complex range of emotions that are ignored than the simple automated categorization of commented emotions by ERNIE, providing not only an accurate categorization of emotions, but also rich insights into the psychological impact of the pandemic. In addition, selecting data only from text posts of Shanghai residents during the lockdown provides a focused analysis that is closely related to geographic and temporal dynamics, resulting in more targeted insights into public behavior under strict quarantine measures.

In addition, by integrating data from Sina weibo, this study expanded the data selection to include data from the full weibo platform for a period of more than four months from before the start of the Shanghai outbreak to its complete end, as compared to a dataset of just one month's worth of user comments on selected TikTok channels used by Che et al. The systematic exclusion of data irrelevant to the study, such as images and advertisements, as well as the strategic merging of similar text, also greatly reduced data noise and improved the relevance of the dataset. This meticulous data organization not only improved the quality of the input data for sentiment analysis, but also enhanced the validity of the study by ensuring that the analysis was based on posts that truly reflected sentiment. By incorporating the impact of specific government policies into the analysis, this study establishes a direct correlation between policy changes and changes in public sentiment, providing valuable causal insights that can guide effective public health communication and policy development during crises.

3.3 Public Emotions and Social Media During Health Crises

In examining the impact of COVID-19 policies on public sentiment across different regions, research findings converge on several key insights while also presenting some unique observations. Wang et al. (2020) and Huerta et al. (2021) both identify fluctuating public support and increased anxiety in response to pandemic measures, such as social distancing and emergency declarations, highlighting the role of social media as a barometer for public sentiment during health crises. These studies underscore the necessity of adaptive policy making, informed by real-time public feedback.

Conversely, Sukhwal & Kankanhalli (2022) provide a more localized perspective by analyzing the specific effects of containment policies in Singapore, showing quantifiable shifts in public sentiment tied to travel restrictions and mask mandates. Their research offers a deeper understanding of the strongly related relationship between policy interventions and public emotional well-being, further emphasizing the critical importance of monitoring and adjusting policies based on public sentiment.

Together, these studies illustrate the interplay between government actions and public perceptions during the pandemic, advocating for the strategic use of social media analytics to guide evidence-based decision-making and policy refinement. They collectively highlight the changes in public sentiment across contexts and the potential for social media platforms to offer valuable insights into the public's emotional responses to governmental measures.

4 Data and Methods

4.1 Data

This study relies on data sourced from Sina Public Opinion Monitoring, a subsidiary of Sina Weibo that offers enterprises and public figures a platform to monitor public opinion trends related to their brand or persona. The platform's primary function is to assist entities in better managing their image or brand promotion and to timely detect public opinion trends for effective crisis public relations management. Therefore, it aggregates and stores a wealth of relevant images and text data from major Chinese social media platforms over recent years.

With authorization from the head of the relevant department at Sina Public Opinion Monitoring, the author of this paper accessed the data using an official staff account, employing a precise search scheme to collect the necessary data. The keywords selected for this study were "epidemic" or "COVID-19," aiming to comprehensively collect posts covering all aspects of the pandemic. To ensure accuracy in our emotion analysis and related research, the location of the posts was strictly limited to Shanghai to ensure that the subjects under study were residents of Shanghai undergoing home quarantine during the epidemic (this requires that the IP address of the posts be located in Shanghai). The time frame for data collection was set from February 24, 2020, to June 30, 2020. This period was chosen to inclusively cover from five days before the first confirmed COVID-19 case in Shanghai to five days after the city announced significant victories in epidemic prevention, ensuring the completeness of the data.

Moreover, in terms of detailed settings, this paper implemented a merging of similar texts to effectively prevent the presence of repetitive texts in the data, which usually come from identical governmental media announcements or posts copied and pasted by various media outlets. The study focused exclusively on text posts, eliminating those containing images, and set filters to exclude noise information, which refers to specific advertisements, such as frequent postings of small ads by marketing accounts.

After making these settings, the paper randomly selected 2,500 posts for each day within the custom time frame, incorporating all available posts for days with fewer than 2,500 posts (this usually occurs before the epidemic starts in Shanghai). Ultimately, 272,624 text data entries were collected, providing a rich dataset for analysis. The meticulousness and thoroughness of this data collection and processing ensure the reliability and validity of the research findings, offering a solid data foundation for a deeper understanding of the emotional changes among residents of Shanghai during the COVID-19 epidemic lockdown.

5 Methodology

5.1 Manual Sentiment Classification

The objective of this phase was to manually classify the sentiments of 2,000 Weibo posts using the Plutchik Emotion Wheel model. This task involved 4 graduate students from top 20 universities in China, chosen for their personal experiences similar to those of the residents of Shanghai during city lockdowns, ensuring a deeper understanding of the context and sentiments expressed in the posts.

The classification was meticulously organized, starting from training the classifiers to defining a clear timeline for task completion. Each emotion defined by Plutchik (1982)—joy, trust, fear, surprise, sadness, disgust, anger, and anticipation—was clearly described in an instruction manual provided to the classifiers. The manual also included examples for each emotion to standardize the classification process.

To ensure consistency and accuracy: - We conducted co-labeling sessions on a subset of the data. - Employed consensus strategies for disagreements. - Introduced mid-term evaluations to check consistency. - The classification results were thoroughly documented and will be used as part of the training set for further model development.

5.2 Training BERT Models

5.2.1 Addressing Data Imbalance

Initially, the dataset exhibited a significant imbalance with a higher prevalence of 'disgust'. To address this, less frequent emotions were grouped into an 'Other' category, resulting in a balanced dataset for six emotion categories: Sad, Disgusted, Neutral, Trust, Anticipation, and Other.

Table 1: Distribution Patterns of Identified Emotions

Emotion	Count	Percentage
Neutral	1541	32.10%
Disgust	894	18.62%
Sadness	820	17.08%
Anticipation	690	14.37%
Trust	445	9.27%
Others	410	8.54%

5.2.2 Model Tuning and Training

The BERT model was fine-tuned with specific focus on: - Learning Rate: Set to 5e-5 for optimal convergence. - Batch Size: Limited to 8 due to memory constraints, ensuring stable updates. - Number of Training Epochs: Limited to 3 to prevent overfitting. - Maximum Sequence Length: Fixed at 128 tokens to capture sufficient contextual information without excessive padding.

A subset of 400 posts was initially used to experiment with these parameters, achieving an optimal accuracy of 43.75%. The final model was then trained on the complete dataset of 2,000 posts, resulting in substantial improvements in accuracy and other evaluation metrics.

5.2.3 Model Predictions

The final phase involved applying the trained BERT model to the complete dataset of over 270,000 Weibo posts, categorizing them into the defined emotion categories. The distribution of sentiments provided insights into the public emotional response to policy changes during the pandemic.

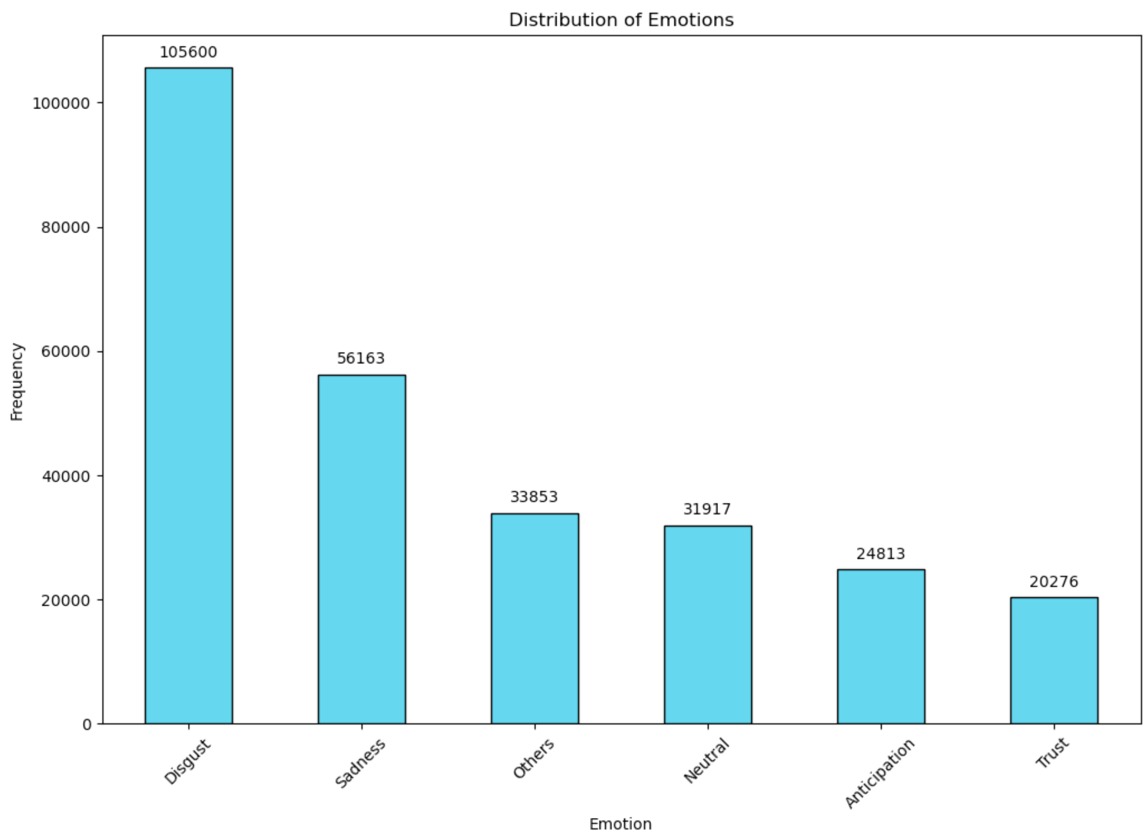

Figure 2: Distribution of emotions

5.3 Data Processing for Time Series Analysis

After modeling, the sentiment classifications were converted into time series data, capturing daily sentiment shifts in response to specific policy events. Six key policy events were coded as binary variables to quantify their impact: - First case reported. - Begin lockdowns. - Measures launched. - Zero case growth. - Work resumed. - Victory declared.

The coding was designed to reflect immediate responses to policy announcements, providing a nuanced view of the public's emotional dynamics in reaction to government actions during the pandemic.

5.4 Time Series Modeling

Using the SARIMAX model, we analyzed the influence of these policy variables on the sentiment trends. This model was chosen for its ability to incorporate seasonal variations and external influences, offering a robust framework for understanding the temporal dynamics of public sentiment in response to the evolving pandemic landscape.

6 Results

6.1Emotional Trends and Model Analysis

6.1.1 Disgust,Sadness

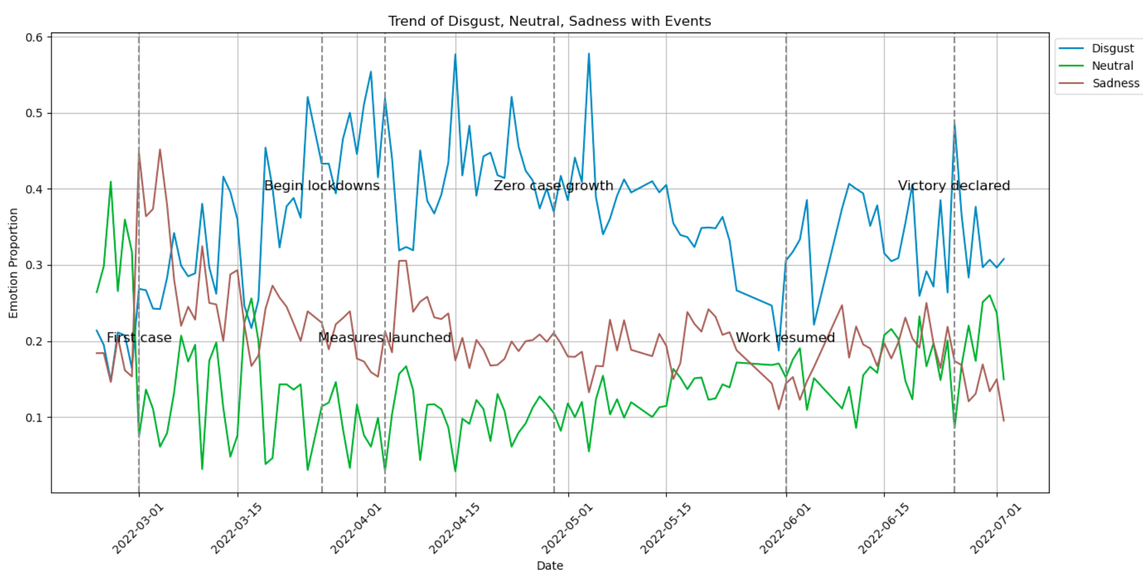

Figure 3: Trend of Disgust,Neutral,Sadness with Events

During the COVID-19 pandemic, the complex interplay between public policy announcements and the emotional responses of the population can be systematically explored through both trend analysis and model validation. This detailed examination is particularly focused on four pivotal emotions: disgust, sadness, trust, and anticipation, each reacting uniquely as the pandemic unfolded through its various phases.

Table 2: Emotional Response Across Policy Events: Disgust, Sadness, and Neutral

Policy Event	Emotion	Coefficient (Std. Err)	AR	MA	Sigma2	P value
First case	Disgust	0.1369*** (0.019)	0.845	-0.9985	6.357e-05	0.000
	Sadness	0.3081*** (0.058)	0.7823	-1.0005	0.0005	0.000
	Neutral	-0.2447*** (0.073)	1.0152	-0.9996	0.0007	0.001
Begin lockdowns	Disgust	-0.0679*** (0.001)	0.9611	86.7668	3.371e-08	0.000
	Sadness	-0.0117 (14.811)	0.9835	-43.5319	3.873e-07	0.999
	Neutral	0.1266 (0.647)	-0.5285	-1.0010	4.914e-05	0.845
Measures launched	Disgust	-0.0562 (0.964)	1.0521	-0.9998	0.0019	0.954
	Sadness	0.0166 (0.041)	0.9625	-1.0011	0.0001	0.689
	Neutral	0.1091*** (0.004)	0.3016	-0.6960	8.027e-06	0.000
Zero case growth	Disgust	-0.0219 (0.176)	1.0253	-0.9996	0.0003	0.901
	Sadness	0.0219** (0.009)	0.9344	0.9953	6.261e-06	0.015
	Neutral	-0.0260 (1.104)	1.0182	-1.0011	0.0002	0.981
Work resumed	Disgust	0.3239*** (0.080)	-0.0934	18.9419	1.445e-07	0.000
	Sadness	0.1387*** (0.009)	0.0193	24.6307	2.536e-07	0.000
	Neutral	0.1801 (0.245)	-0.1495	8.2701	9.394e-07	0.462
Victory declared	Disgust	-0.0750 (0.405)	1.0217	-1.0001	0.0070	0.853
	Sadness	0.0694 (0.349)	0.8577	1.0005	0.0014	0.842
	Neutral	0.1143 (0.107)	0.7970	-1.0002	0.0015	0.286

Disgust: The emotion of disgust showed a pronounced increase upon the reporting of the first COVID-19 case. This response was quantitatively confirmed in the 'first case' model, which returned a coefficient of 0.1369. This statistic indicates a strong linkage between the initial public announcement and a subsequent rise in disgust, highlighting the immediate shock and repulsion felt by the public. During the lockdown, this emotion remained at elevated levels, signifying ongoing concerns about the rapid spread of the virus. The announcement regarding the resumption of normal activities marked another significant uptick in disgust, as seen in the 'work resumed' model, where the coefficient surged to 0.3239. This increase not only confirms the initial observation but also underscores a broad dissatisfaction with how the pandemic was managed and a lingering uncertainty about the future.

In the context of the disgust emotion, it is noteworthy that the coefficient for 'work resumed' stands at 0.3239, which is in stark contrast to the expected decrease in disgust following the resumption of work. Among the many posts expressing disgust published within three days after the announcement of work resumed, I have selected the following 10 typical posts:

“I just did a nucleic acid test the day before yesterday, and today we were notified to do it again. When the epidemic was severe, we tested every four days. Now there’s no epidemic, and it’s every two days. There’s another round of testing for all staff in a few days. We will have done four or five tests in six days. Are people in Shanghai even this diligent? Who’s using the epidemic as an excuse to waste national resources?” (Posted June 1, 2022).

“Only a few village officials were dealt with; the epidemic in Shanghai was caused by their ineffective epidemic prevention.” (Posted June 2, 2022).

“Returning to work is easy, restarting production is hard. Just handing out money and tax breaks, the common people can hardly bear it anymore. What else is there to cut?” (Posted June 3, 2022).

“I’m really not feeling happy about this. The impact of the pandemic has been too great, not just on a daily life level.” (Posted June 1, 2022).

“Shanghai has unsealed, which is a cause for happiness, but the Shanghai government needs to summarize lessons. Why did you manage the epidemic worse than other places? Why do many at the grassroots level not follow instructions? Why break the universal standard and not designate high-risk areas? Especially during the epidemic, how many problems arose with medical treatment and supply of materials, has anyone come forward to take responsibility? Shouldn’t you apologize to all the people of Shanghai? The media also needs to reflect. Why are you so concerned about reporting problems in other places but only report good news when it comes to Shanghai?” (Posted June 1, 2022).

“Finally, Shanghai is back, welcome! But now it’s really time to thoroughly hold accountable those responsible for the uncontrolled epidemic that caused Shanghai to shut down for months! Was it caused by the general grassroots epidemic prevention staff not performing their duties seriously, or was it the few epidemic decision-makers who caused such adverse outcomes? This question must be clarified and taken as a lesson!” (Posted June 2, 2022).

“Congratulations on the full resumption of work in Shanghai. But to be honest, friends in Shanghai should try to stay in Shanghai as much as possible, non-essential travel out of Shanghai is not advised. After this wave of the epidemic, Shanghai’s epidemic data has lost credibility in the eyes of other provinces and cities, and this loss of credibility has spread to many other areas, recovery will take time.” (Posted June 3, 2022).

“Isn’t it owed to all the people of the city to apologize? Those innocently wronged who died in the epidemic are just forgotten like that? One word of unsealing, and everything is turned over?” (Posted June 1, 2022).

“The Shanghai government will never be able to apologize to those who died indirectly because of the lockdown, only the people of Shanghai will remember them. For the government, these deceased are just numbers to be removed from the COVID-19 death count." (Posted June 2, 2022).

"The epidemic is like a magic mirror, showing the demons and monsters of great Shanghai, from bottom to top!" (Posted June 3, 2022).

The counterintuitive rise in negative sentiment from the above posts can be attributed to several factors.

Firstly, the management of the pandemic and the communication strategies adopted by the authorities may not have met the public's expectations. The sudden shift from a state of lockdown to work resumption could provoke unease, with doubts about whether the current systems are prepared to handle potential post-lockdown outbreaks and ensure public health.

Secondly, the sustained disgust during the lockdown reflects deep concerns over the immediate health risks of the pandemic and its long-term socio-economic impact. As work resumes, these worries are not automatically dispelled but instead accumulate as everyday life gradually resumes.

Moreover, public attention is sharply focused on the accountability and transparency of the measures taken during the pandemic. The heightened disgust may also indicate the public's perception that the government has not provided adequate compensation for the difficulties suffered by citizens and feels a sense of injustice about the disparate impacts of the pandemic on different segments of society.

Sadness: In the early days of the outbreak, the confirmation of the first case triggered a sharp increase in sadness, as captured by a coefficient of 0.3081 in the corresponding model. This reflects the direct emotional impact of the health crisis on the populace. As restrictive measures such as city-wide lockdowns were implemented, sadness experienced fluctuations but generally trended downward, indicating a gradual acclimatization to the new norms and perhaps a subdued hope as people adjusted to the prolonged crisis. The model titled 'victory declared', which recorded a relatively low coefficient, suggests that the announcement of significant progress in controlling the pandemic did lead to a decrease in sadness, though the change was not highly significant statistically, suggesting a cautious optimism rather than outright relief.

There's an intriguing point to explore within the emotion of sadness: following the announcement of the 'first case,' the coefficient for sadness was 0.3081, a substantially high coefficient for sadness. It is therefore essential to investigate what exactly the citizens of Shanghai were grieving over at that time. Here are six very typical examples I have selected:

"With the outbreak in Shanghai, everyone's now queuing for nucleic acid tests, right? [dog] [dog] [dog] Such a grand spectacle, I'm exhausted." (Posted March 3, 2022).

"I had everything ready for my trip, and now you hit me with a travel ban because of the cases in Shanghai [heartbreak]. Need to redo all my travel plans." (Posted March 2, 2022).

"Came to Shanghai this morning, and by the afternoon, the outbreak news broke [sick] [sick] [sick]." (Posted March 1, 2022).

"In two days, am I even going to be able to visit Disney? [tears]" (Posted March 3, 2022).

"Shanghai is reporting cases again, can we still fly out? I've already booked flights and hotels, what about quarantine?" (Posted March 2, 2022).

"I had just left Shanghai and then an outbreak pops up again, and I am flagged... It happened last time too, I was due to leave the next day, and the outbreak occurred in the evening. I was so afraid I wouldn't be able to fly out, I went for a nucleic acid test in the middle of the night! [sad]" (Posted March 1, 2022).

The emotions within these posts primarily reflect sadness about the disruption to societal norms and individual lives. In these posts, we observe very representative concerns, including anxiety over the frequency of nucleic acid testing, sorrow over disrupted travel plans, and worries about the sudden emergence of the epidemic and restrictions on daily activities. The content of these posts reveals the continuity of public sentiment during the epidemic and how people improvised in response to the constant changes.

6.1.2 Trust, Anticipation

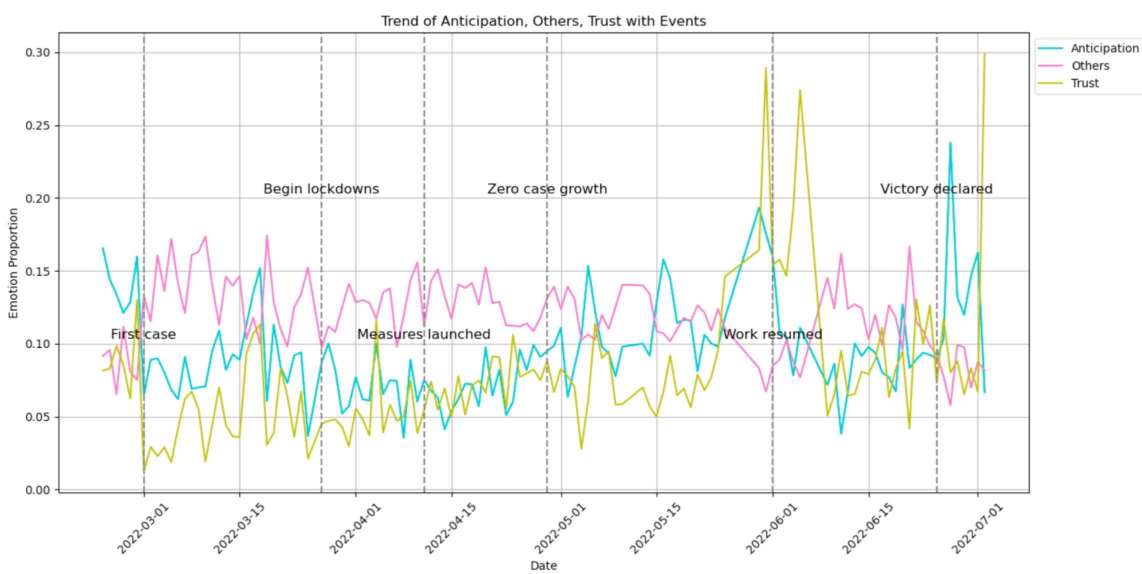

Figure 4: Trend of Anticipation, Trust,Others with Events

Trust: The emotion of trust exhibited fluctuations throughout the pandemic, as indicated by the statistical data from various policy interventions. In the initial phases, as

Table 3: Emotional Response Across Policy Events: Trust, Anticipation, and Others

Policy Event	Emotion	Coefficient (Std. Err)	AR	MA	Sigma2	P value
First case	Trust	-0.1001 (0.817)	0.845	-0.9985	6.357e-05	0.902
	Anticipation	-0.0972* (0.038)	1.0881	-1.0010	8.087e-05	0.010
	Others	0.0903 (4.342)	0.8831	0.9981	0.0005	0.983
Begin lockdowns	Trust	0.0480*** (0.001)	-0.2628	10.0281	3.637e-08	0.000
	Anticipation	0.0897 (0.050)	8.3332	2134.9637	7.64e-09	0.076
	Others	0.1096*** (0.001)	-0.0848	35.0243	1.378e-09	0.000
Measures launched	Trust	0.0559*** (0.013)	0.4033	-1.0010	5.621e-05	0.000
	Anticipation	0.0333** (0.009)	0.7090	0.9959	5.401e-06	0.000
	Others	-0.0563*** (0.015)	1.1031	-0.9988	2.818e-05	0.000
Zero case growth	Trust	0.0142 (0.061)	0.9272	-0.9991	5.615e-05	0.816
	Anticipation	0.0211 (0.022)	0.9895	-0.9986	3.937e-05	0.330
	Others	0.0211 (0.022)	0.9895	-0.9986	3.937e-05	0.330
Work resumed	Trust	0.1520*** (0.003)	0.0054	56.5344	7.151e-09	0.000
	Anticipation	0.0952 (0.184)	0.3455	-15.0481	3.078e-09	0.605
	Others	0.0155* (0.006)	1.0465	44.0663	3.078e-09	0.011
Victory declared	Trust	0.0337 (0.088)	0.8447	-1.0002	0.0003	0.701
	Anticipation	-0.0021 (0.014)	0.8697	1.0025	1.628e-05	0.887
	Others	-0.0021 (0.014)	0.8697	1.0025	1.628e-05	0.887

the first cases were reported, trust saw a slight decrease (coefficient of -0.1001), suggesting initial public uncertainty despite timely communication from government bodies. Trust notably increased (coefficient of 0.0480) during the enforcement of lockdowns, reflecting a growing confidence in the government's decisive actions. As measures began showing effectiveness, particularly when the community first achieved zero new cases, trust did not significantly change (coefficient of 0.0142), indicating a sustained but cautious optimism. The substantial rise in the trust coefficient to 0.1520 in the 'work resumed' model signifies a robust reinforcement of public confidence as normalcy began to return and the government's management efforts were viewed more favorably.

Anticipation: Initially, anticipation declined with the onset of the pandemic, as evidenced by a negative coefficient of -0.0972 at the 'first case' stage, reflecting significant public trepidation about the future. As lockdown measures took effect, a slightly positive but not statistically significant change in anticipation (coefficient of 0.0897) was observed, suggesting a cautious hopefulness as the public adjusted to new norms. However, the transition to zero case growth did not bring a significant change in anticipation (coefficient of 0.0097), indicating a plateau in emotional response despite positive developments. A slight but not statistically significant increase in anticipation (coefficient of 0.0952) in the 'work resumed' model indicates a tempered but growing optimism about the future as the crisis seemed to be abating.

These trend analyses help trace how various policy milestones and pandemic developments have intricately influenced public emotions. This comprehensive approach offers valuable insights into the dynamics of emotional responses in crisis management, enriching our understanding of the pandemic's impact on societal emotions and enhancing our capability to predict and manage public sentiment in future crises.

7 Discussion

In the discussion section of this graduate thesis, by analyzing in detail charts and models of changes in public sentiment in Shanghai during the COVID-19 pandemic, I provide a nuanced view of how a variety of emotions reacted during a major policy change and public health crisis. This exploration provides key insights into understanding how the unfolding events of the epidemic affected public sentiment and offers some counterintuitive findings that challenge intuitive perceptions about public sentiment during the new crown crisis.

7.1 Detailed Analysis of Emotional Changes

The analysis of emotional responses presented in the paper includes a comprehensive analysis of how specific emotions changed in response to key policy interventions such as the notification of the first COVID-19 case, the initiation of the citywide lockdown, and the eventual reopening. The data reveal patterns of fluctuations in public sentiment in response to changes in public health directives.

Key Emotional Responses:

- Disgust: This emotion intensified notably in response to critical policy declarations and during pivotal moments of the outbreak. Initially, as the first case emerged, there was a significant uptick in disgust, signaling public unease and distress about the abrupt and stringent changes to daily life. Disgust reached another high as restrictions were eased and societal functions were reinstated, likely driven by public disapproval over outbreak handling, concerns over hasty lifting of precautions, and trepidation of a possible resurgence of the virus.

- Sadness: peaks at the beginning of the outbreak and fluctuates as events unfold. Findings suggest that sadness is not only a direct response to a health crisis, but is also associated with broader social-economic impacts, including concerns about economic security such as the stability of employment and the ability to repay loans, such as mortgages, and the stability of the family as work resumes.

Other emotions:

- Anticipation: the initial drop may signify a decrease in positive outlook for the future. This trend briefly reversed after the announcement of substantial progress in controlling the outbreak, but dipped again after the resumption of daily activities.

- Trust: This sentiment showed a consistent pattern, yet it saw a significant rise once the milestone of zero new cases was achieved, indicating amplified trust in the efficacy of public health directives. Nevertheless, as daily life began to normalize, trust experienced some instability, suggesting persistent ambivalence and critical views regarding the handling of the outbreak. The considerable elevation in trust observed with a coefficient of 0.1520 in the 'work resumed' model underscores a marked reinforcement of public assurance, reflecting optimism in government management as activities resumed.

- Emotional categories labeled as other, including complex emotional responses such as anger, surprise, and happiness, were relatively stable during the outbreak, but experienced slight fluctuations during major event announcements, reflecting a wide range of nuanced emotional responses to the development of the outbreak.

7.2 Implications of counterintuitive findings

Through a detailed analysis of social media posts under the hashtags disgust and sadness during the announcement of the first COVID-19 case and the subsequent resumption of work, this paper provides a deeper understanding of the complex psychological and emotional landscape during the outbreak. The observed increase in negative emotional responses at times when the urgency of the pandemic was expected to diminish (e.g., during the lifting of lockdowns and the resumption of work) suggests that public reactions to outbreak management are influenced by more than just fear of the virus. These reactions also reflect perceptions of the government's ability to effectively implement policies, the degree of care for people's livelihoods, and the potential impact of individuals' economic situations and psychological well-being on their emotions. This analysis offers a nuanced view of how various factors shape public sentiment during critical phases of the pandemic.

7.3 Limitations

The primary limitation of the model stems from the interdependence of emotional responses, whereby variations in one affective state are not solely attributable to contemporaneous pandemic-related events or policy enactments but are also influenced by shifts in other emotions. For instance, the observed increase in sadness during the 'measures launched' phase cannot be exclusively ascribed to the policy announcement; it is concurrently affected by a proportional decrease in disgust within the composite emotional landscape of that period. This interplay complicates the task of disentangling the intricate relationship between individual emotions and policy interventions, presenting a significant challenge in the analysis.

Additionally, the construction of the model presents limitations. This study employs a relatively simple binary variable method to code the policy variables (1 if the policy is being implemented, and 0 if it is not). Given that the events selected for this study are spaced out over time, to ensure the model's results accurately reflect the impact of policy announcements on sentiment, the study could only select a total of six data points from the three days before and after each policy announcement. This constraint significantly reduces the reliability of the results.

Moreover, the data for this study was sourced solely from the Weibo platform, which may lack diversity. While it is reasonable to collect data from Weibo, given its focus on the instant dissemination of information, public discussion, and a relatively balanced age distribution of users, it is also crucial to consider other popular social platforms, such as Douyin and Xiaohongshu. Douyin's primary user base is young people aged 18 to 30, particularly Generation Z, who prefer rapid content updates and diverse formats. Xiaohongshu's user base consists mainly of young women aged 20 to 30, focusing on lifestyle sharing. During the pandemic's city lockdown, Shanghai's population was predominantly young office workers. Including data from these two platforms would effectively expand the diversity of the study.

7.4 Policy recommendations and future research

The findings of this study emphasize the need for policymakers to consider emotional and psychological impacts as a central part of decision-making when considering public health responses. Effective communication, empathetic public engagement, and implementation of staged policy changes are critical to managing disease and public emotional health.

In addition, future research should continue to explore these dynamics, potentially through the integration of more direct feedback mechanisms to assess public mood in real time and help tailor interventions to be more adaptive and sensitive. Ongoing research exploring the emotional impact of public health policies will also help prepare for future public health crises by ensuring that physical and psychological resilience are addressed simultaneously.

8 Conclusion

This thesis offers a nuanced understanding of the interplay between public health interventions and emotional responses during an unprecedented global health crisis. Research findings indicate that negative emotions such as disgust and sadness increase significantly during adverse events like the initiation of lockdowns; conversely, positive emotions like trust see a certain degree of increase after favorable events such as the resumption of work. Additionally, the study discovered a substantial rise in the proportion of disgust following the work resumed announcement. This increase stems from the people of Shanghai's dissatisfaction with the sudden lifting of the lockdown leading to potential health risks, discontent with the government's mismanagement during the lockdown, and concerns over their economic repayment capabilities and employment. This paper aims to provide theoretical support for the Chinese government in addressing the next public health crisis, based on the findings of this study. By meticulously analyzing the changes in emotions among residents of Shanghai, it not only enriches the field of emotional analysis within public health but also provides strategic insights for navigating urban crises and formulating empathetic, responsive public policies. As the world continues to address and eventually move beyond the COVID-19 pandemic, the lessons learned from this research will be invaluable for future crisis response strategies, ensuring that public health measures take into account their profound psychological impacts on communities.

Data and Code Availability Statement

The data and code supporting the findings of this study are openly available in the GitHub repository located at https://github.com/GuangjieXu/thesis-data. This repository contains all necessary data files, analysis scripts, and detailed instructions required to reproduce the results and analyses presented in this thesis.

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Appendix

1. Project overview

Objective.

The purpose of this project is to classify the sentiment of 2,000 Twitter posts using the Plachico Sentiment Wheel model, and the final results will be used as the training set needed to analyze the data for my graduate thesis.

Task Importance

This classification task is a critical step in constructing the training set required for the thesis, and its accuracy directly affects the validity and reliability of the study.

2. Introduction to Plutchik's Emotion Wheel Theory

Background.

Psychologist Robert Plutchik's Emotional Wheel (Plutchlt), a theory that focuses on the fact that when emotions are expressed at different intensities, the emotions interact with each other to produce different emotions and establish new emotional states.Robert Plutchik's Psychological Evolutionary Theory of Emotion is one of the most influential taxonomies of common emotional responses. He believed that there are 8 most basic emotional elements - Anger, Fear, Sadness, Disgust, Wonder, Curiosity, Acceptance and Joy.

1. Each petal represents a category of emotion. The darker the color, the heavier, or more saturated, the emotion. The lighter the color, the lighter and more empty the emotion. For example: the red petals on the left go from worry, to anger, to rage; the yellow petals on the top go from serenity, to happiness, to ecstasy, etc. The darker the color, the more gaps are left. The further inward and darker the color, the more saturated the emotion. The innermost circle is completely solid.

2. Two opposite petals represent opposite emotions. The four bright shades in the upper left are positive emotions, and the four dark shades in the lower right are negative emotions.

3. Task flow and assignment

Classifier Assignment:

A total of four classifiers were designed for this task, with each of the two being responsible for 1,000 randomly selected non-duplicated posts from 120,000 microblog postings.

Schedule.

Task start date: January 10, 2023

Progress checkpoint: January 17, 2023

Task completion date: January 24, 2023

Schedule over the two-week period:

Week 1 (January 10th - January 17th):

The first two days focus on understanding and practicing exercises on the classification criteria. The following five days are spent beginning the categorization task.

Interim checkpoints were used to assess progress and to ensure that a total of 800 pieces of data had been graded, as well as to ensure that all classifiers had uniformly correct classification criteria.

Week 2 (January 17th - January 24th):

Continue to categorize posts, increasing the pace to ensure the task is completed on time.

Conduct random sampling during the last days of the task to ensure that the results obtained are overwhelmingly correct.

4. Categorization Criteria and Guidelines

Detailed Guidelines

Joy (Joy):

DEFINITION: A pleasurable emotional state, usually expressed as happiness, contentment, or excitement.

EXAMPLE: ”Today was great! I just found out I passed an important test! #SuperHappy”

Trust:

DEFINITION: An emotional state of dependence on or belief in another person that involves reliance on the reliability, honesty, and friendliness of another person.

EXAMPLE: ”Whenever I feel lost, I always turn to my friends, whose advice is always so pertinent. #TrueFriends ”

Fear (Fear):

DEFINITION: A reaction to a real or potential threat, usually characterized by anxiety, uneasiness, and worry.

EXAMPLE: ”I’ve heard that there are robbers in the neighborhood lately, and whenever it’s late at night, I feel uneasy and scared. #Safety first”

Surprise (Surprise):

DEFINITION: A reaction to an unexpected or unanticipated event, usually accompanied by shock or surprise.

EXAMPLE: ”I just received an unexpected birthday gift from my old classmate, and I didn’t expect him to remember it! #surprise”

Sadness (Sadness):

DEFINITION: An emotion resulting from a loss, setback, or unfortunate experience, often accompanied by feelings of melancholy, emptiness, or helplessness.

EXAMPLE: ”Said goodbye to my pet dog today, who had been with me for ten years. Heart overwhelmed with loss and sadness. #EverMissed ”

Disgust (Disgust):

Definition: an emotion of intense dislike or revulsion for something or behavior.

EXAMPLE: ”It’s disgusting to see people littering on the streets. #Environmentally conscious.”

Anger (Anger):

DEFINITION: A strong emotional response to injustice, frustration, or threats, usually expressed as anger or rage.

EXAMPLE: ”I encountered another queue-jumper on the bus, and this disregard for the rules made me very angry. #Civilized travel.”

Anticipation (Anticipation):

Definition: an anticipation and anticipation of future events, often accompanied by a sense of curiosity and excitement.

EXAMPLE: ”Tomorrow is my interview day and feel both nervous and anticipatory. I hope everything goes well! #GoGo.”

5. decision-making rules

Principle of Consistency:

If two classifiers give the same emotion classification result, then that result is used.

Neighboring Emotions Rule:

If two classifiers give emotion classification results that are adjacent on the emotion wheel, then both emotions are recorded.

Divergence Resolution:

If the classification results given by two classifiers differ significantly, then a third classifier will make the final decision.

6 Data Recording and Management

Recording Format

The randomly selected tweets will be stored in two excel sheets and copied into four, each sheet has 1000 tweets, the classifiers who are assigned to the same sheet will categorize their own excel sheet according to the eight basic sentiments and upload them after commenting.

Organize the data

I will organize the results and review each posting to see if the results meet the criteria based on the decision rules.