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News media in crisis: a sentiment and emotion analysis of US news articles on unemployment in the COVID-19 pandemic

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News media play an indispensable role in disseminating information and shaping public perception during times of crisis. This study, integrating sentiment, emotion, discourse, and timeline analyses together, conducts a corpus-based sentiment analysis of the news articles on unemployment from *the New York Times* in 2020 to capture the emotional dynamics conveyed by the newspaper as the pandemic-induced unemployment developed in the US. The results reveal that positive sentiment in the news articles on unemployment is significantly higher than negative sentiment. In emotion analysis, "trust" and "anticipation" rank the first and second among the eight emotions, while "fear" and "sadness" top the negative emotions. Complemented with a discourse analysis approach, the study reveals that the change of the sentiments and emotions over time is linked with the evolution of the pandemic and unemployment, the policy response as well as the protests against ethnic inequalities. This study highlights the important role mainstream news media play in information dissemination and solution-focused reportage at the time of severe crisis.

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Introduction

The COVID-19 pandemic has wrought a devastating impact on all facets of human life, particularly on health, economy, and psychology. Detected at the end of 2019 and exponentially sweeping across the world in the first months of 2020, it was reported to have taken about 7 million lives till mid-August, 2023 (WHO, 2023). In the first two years of the pandemic, it was identified as the third leading cause of death in the United States (CDC, 2022). In response to the pandemic, strict social-distancing restrictions have been implemented in the US and globally, which crippled business activities in various sectors (Fairlie, 2020). The enactment of the social-distancing restrictions and the shutdown of business activities have had a strong impact on unemployment (Morris et al., 2023).

The pandemic, in addition to causing death and illness, has led to unprecedented hazards to mental health globally. Relatively high rates of symptoms of anxiety, depression, distress, and stress are reported in the general population during the COVID-19 pandemic (Xiong et al., 2020). The psychological hazards are compounded by unemployment concern that has significant adverse impact on psychological function. In fact, ill mental health brought by pandemic-elicited unemployment is considered as the most alarming and revealing problem that characterises the current crisis (Bocchino et al., 2021).

The devastating consequences of the pandemic have made it the focus of many sentiment analysis studies, most of which targeted at public emotions on social media concerning a variety of issues (Nia et al., 2022a; Sukhavasi et al., 2023; Mohamed et al., 2023). No attempt, however, has been made studying the public perception of unemployment conveyed in mainstream news media during the crisis using the combined approach of sentiment analysis and corpus-based discourse analysis. Based on a corpus of unemployment-related news articles in *the New York Times* in 2020, this study, integrating sentiment, emotion, discourse, and timeline analyses together, hopes to explore how the pandemic-induced unemployment was represented emotionally on news media, and how the sentiments and emotions changed over time with the evolution of pandemic and unemployment.

Literature review

Sentiment analysis is the study of emotions, opinions, appraisals, and attitudes regarding “services, products, individuals, organizations, issues, topics, events and their attributes” (D’Andrea et al., 2015: 27). Various methods have been adopted in conducting sentiment analysis, which in general, can be classified into supervised/machine learning approach and the unsupervised/lexicon-based approach. The first approach uses classification algorithms to identify the sentiment of a text, mainly for determining the polarity of a target document via automatic computing (Lei and Liu, 2021). In lexicon-based approach, a sentiment lexicon, which is a word list that contains the target sentiment words coded as positive, negative, or neutral, along with their respective level of strength or intensity, is used as the main tool for sentiment identification and classification (Lei and Liu, 2021). Nowadays, there has been a trend for the use of a hybrid method in sentiment analysis, such as in Domalewska (2021) and Mohamed et al. (2023).

As the pandemic has brought global financial instability and reductions in per capita income, creating the greatest global economic slump since World War II (World Bank, 2020), its impact on economy and unemployment has been one of the most important and persistent topics on media of all forms throughout the world in 2020. Its adverse effect on job safety and income loss is most immediately reflected in social media which have become the data sources for many sentiment analysis studies. Based on the sentiments of the Twitter data, Nia et al. (2022a) compared and analyzed the macroeconomics of three different countries with distinct income levels, Nigeria, South Africa and Canada. It showed that at the beginning of the pandemic the unemployment rate increased for all the three countries, while lower-middle-income countries could be more vulnerable to lockdowns and economic restrictions. Sukhavasi et al. (2023), using VADER Sentiment Analyzer, presented an analysis of Twitter data related to economy during COVID-19 outbreak, and identified how underlying sentiments had varied with respect to time, gender, and geographies before and during pandemic in terms of economy, employment, money, and jobs. Nia et al. (2022b) nowcasted the unemployment rate of South Africa based on a machine learning approach to analyzing the sentiments on tweets, finding the number of tweets had a high correlation with the unemployment rate, while the social sentiments of the tweets were negatively correlated with the unemployment rate. Mohamed et al. (2023), using LexDeep, a hybrid sentiment analysis technique, on tweet data before and during the pandemic in Malaysia, Saudi Arabia, and globally, found that an increase in the unemployment rate immediately after the outbreak of COVID-19 affected the global population.

Sentiment analysis can also reveal public perception of the government’s efforts to combat economy and unemployment problem during the COVID-19. Maulana et al. (2022), using three algorithms, found that in general the public has a positive attitude to the efforts and policies the Indonesian government took to overcome unemployment. Domalewska (2021), using mixed-method approach to analyzing big data from tweets and Facebook posts related to the mitigation measures, found that the implementation of the anti-crisis measures triggered a barrage of criticism pointing out the shortcomings and ineffectiveness of the solutions, while the revised relief legislation decreased negative sentiment.

So far, sentiment analysis studies on public perception of the economy, job safety, and government response are generally based on the data from social media. Except for several studies focusing on public perception of the pandemic expressed on news media, such as Krawczyk et al. (2021) and Aslam et al. (2020), no attention, to date, has been paid to the sentiments on unemployment conveyed on mainstream news media. As social media and mainstream media play divergent and complementary roles in terms of social reality construction in that the former is more centered on individual communication while the latter pays more attention to the overall description of the present (Schrape, 2018), it is highly significant to examine the attitudes and feelings conveyed on the mainstream news media to job safety in 2020, and their change over time as the pandemic and unemployment evolved.

For sentiment analysis of the corpus in this study, NRC (Mohammad and Turney, 2013), a lexicon-based approach, is adopted to identify sentiments and emotions from texts. The NRC Emotion Lexicon is programmed with more than 14,000 unigrams and 25,000-word senses in English (Hao et al., 2022). Moreover, NRC provides not only two polarity sentiments, but also eight basic emotions based on Plutchik’s (1980) Wheel of Emotions, which allows us to make a more fine-grained analysis of the feelings in the news articles.

As a complement to the lexicon-based approach to sentiment analysis which is flawed with the neglect of context (Khoo and Johnkhan, 2018), a corpus-based discourse analysis is adopted. The goal of using methodological triangulation (Egbert and Baker, 2019) is to identify the significant themes and events linked to the sentiments and emotions. By combining the two methods and timeline analysis of the unemployment-related news articles in 2020, we hope to find answers to the following three questions:

(1) What sentiments and emotions were conveyed in the news articles on the pandemic-elicited unemployment in 2020?
(2) How did the public's sentiments and emotions fluctuate over time with the evolution of the pandemic and unemployment?
(3) What significant events and themes, based on the corpus-based analysis of the news texts, are linked with the emotions conveyed on the news media?

Methods

Data collection. The study is based on the news reports from *the New York Times* (NYT). This newspaper was selected for the following reasons. First, it is the most popular newspaper among US digital news consumers and one of the major internationally recognized US mainstream newspapers (Pengue, 2023; Hou and Peng, 2023). Second, it has been one of America's most trusted newspapers in American history (Pengue, 2023), with notable influence on the content of other mass media and coverage of international news (Gitlin, 1980). The news articles for the corpus of the study were obtained via LexisNexis which archives both online and print versions of newspapers. The words related with unemployment, including "layoff*", "lay* off", "laid off", and "unemploy*", were utilised to search articles in NYT in which each term was mentioned at least once, from 1 January, 2020 to 31 December, 2020. The initial year of the pandemic was chosen because in this year unemployment rates reached unprecedented levels worldwide due to lockdown measures and business closures (Nicola et al., 2020), bringing about significant adverse effects on people's mental health (Bocchino et al., 2021). The corpus comprises 4921 news articles, totaling 8,016,170 words. The articles of each month were put in a subcorpus for later calculation and analysis.

Text purification and cleaning. After the news reports were collected, the articles about countries other than the US were removed manually. Text cleaning procedure was conducted with Python, including lowercasing, tokenization, lemmatization, part-of-speech tagging and removing unnecessary information such as duplicate articles, URL addresses, punctuation, stop words and non-English characters.

Extraction of sentiments and emotions. The sentiments and emotions extraction was based on NRC Emotion Lexicon, a list of English words annotated with polarity sentiments (positive and negative) and eight emotions (anger, anticipation, surprise, trust, disgust, fear, joy, and sadness) (Mohammad and Turney, 2013). Python scripts were used to match words in a subcorpus with their closest associated emotions. The calculation is conducted on the 12 subcorpora independently on a monthly basis, so that we could track the trajectory of sentiments and emotions at the different stages of the pandemic and unemployment.

Corpus-based discourse analysis. As a complementation to sentiment and emotion analysis, the corpus-based approach to discourse analysis was applied. Drawing on the basic corpus linguistics techniques, including analysis of frequencies, collocates, colligation, and clusters (Baker, 2023), we hope to identify significant events or themes associated with emotions conveyed on the news media. As it was impossible to check the uses of all the lexical terms tagged with the emotions, we concentrated on the contexts of high-frequency terms. Using the NRC Emotion Lexicon, Python generated a monthly list of the top 10 lexical items linked to each of the eight emotions. Consequently, we obtained 12 high-frequency word lists for each emotion upon analyzing all subcorpora. Since the high-frequency words varied from month to month, we focused on the terms that appeared at least 4 times across the 12 lists, so as to identify the most influential events or prevalent themes in 2020 associated with each emotion. Employing AntConc, we examined their frequencies, colligations, collocates (measured by likelihood), and clusters, if necessary, to pinpoint what they meant in the context.

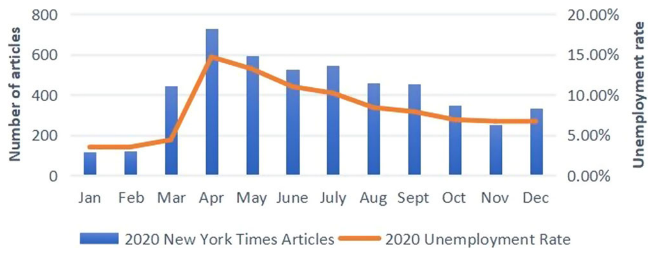

Fig. 1 The number of articles on job loss in NYT and unemployment rates in 2020. The blue bars denote the numbers of unemployment-related news reports on NYT in 2020, indicated with numerical values listed on the left y-axis. Meanwhile, the orange line depicts the unemployment rates, represented as percentages displayed on the right y-axis. The horizontal axis denotes the twelve months of 2020.

Results and discussion

Correlation between news coverage and unemployment. The large scale business closures and job losses brought about by the containment measures for the COVID-19 pandemic have made job safety one of the focuses of news media in 2020. Figure 1 below presents the news coverage of NYT on job loss and the unemployment rates given by American Labor Force in 2020.

The speedy spread of the pandemic has led to the spike of unemployment rates in the US and the world. After the declaration of a national emergency on 13 March, 2020 by President Trump and the enactment of a wide range of social distancing interventions across the country, the unemployment rate rose from 4% in March to a peak of 14.7% in April—the highest since the Great Depression and the largest over-the-month increase in the history of the data (Bureau of Labor Statistics, 2020).

A similar change was detected in the coverage of unemployment in NYT. March of 2020 saw a substantial increase in the number of unemployment-related articles, and a dramatic rise in coverage occurred in April when the highest unemployment rate and the peak for patient numbers (CDC, 2023a) were recorded. This surge in media coverage underscores the media's role in promptly reflecting the urgency of the pandemic and its impact on unemployment. It also highlights a rather generalizable pattern in economic news reporting: negativity bias—the tendency to systematically devote more attention to negative as compared to positive economic trends (Damstra et al., 2018). The results of Pearson's correlation show the news coverage in NYT and the unemployment rates in 2020 were significantly correlated ($r = 0.868$, $p = 0.00 < 0.05$).

Sentiment analysis. Sentiment analysis of the news articles presents a classification of polarities conveyed by the newspaper. Table 1 below is the descriptive statistics of the sentiment analysis of the corpus, and Fig. 2 presents the trajectory of the sentiments with the passage of time in 2020.

Based on Table 1 and Fig. 2, we can draw some conclusions regarding the sentiments expressed in the unemployment-related news articles. First, despite its rises and falls, positive sentiment is

Table 1 Descriptive statistics of the sentiment polarities in the corpus.

ID	Sentiment	Mean value	Sentiment S.D.
1	positive	0.050917	0.001441
2	negative	0.033083	0.001382

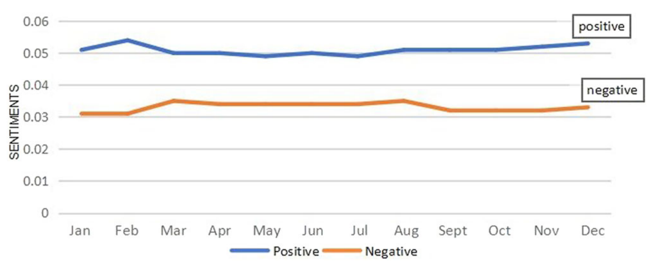

Fig. 2 Positive and negative sentiments in NYT unemployment-related news articles in 2020. The x-axis of the chart represents the twelve months of the year, while the y-axis displays the polarity sentiments' valence.

significantly higher than negative sentiment throughout the year. This result is different from those of the several studies analyzing the sentiments on unemployment-related social media posts. In Nia et al. (2022b), tweets with negative sentiment were more than with positive sentiment, and Sukhavasi et al. (2023) found that negative sentiment is higher in the first three months of 2020. The causes of the differences will be examined in the discussion part.

Second, there is an evident and logical interaction between the two polarities as they change over time with the evolution of the pandemic and unemployment. Generally, when the positive sentiment rises, the negative one falls. The results of Pearson's correlation show that there is a significant negative correlation between the polarities regarding the unemployment in 2020 ($r = -0.624$, $p = 0.03 < 0.05$).

A closer look at the tracks of the two sentiments shows they experience three notable changes along the timeline. The first turning point occurs in February when the positive sentiment begins to fall and the negative sentiment begins to rise, the time when the pandemic was dubbed "COVID-19" by WHO. The second turning point appears in March when the decline of positive sentiment and the rise of the negative are curbed and remain stable in the forthcoming five months. The third turning point occurs in August when the positive sentiment begins to climb and the negative starts to fall slowly till the end of 2020.

Emotion analysis. Based on NRC Word-Emotion Association Lexicon (Mohammad and Turney, 2013), eight emotions are measured in this study. The descriptive statistics of the eight emotional values in the corpus are reported in Table 2, and Fig. 3 presents the change of the eight values over time in 2020 in NYT unemployment-related news articles.

The results show that the unemployment-related news articles in NTY in 2020 contain all the eight emotions included in the NRC emotion lexicon. The value of "trust" ranks the first among the eight emotions, followed by "anticipation," "fear," "sadness," "joy," "anger", "surprise", and "disgust". It is noticeable that, in general, all the eight emotions, in conformity with the sentiment polarities discussed above, experience the same fluctuations at the three turning points: February, March, and August, although the change in August is not conspicuous in some emotions like "disgust".

Table 2 Descriptive statistics of the eight emotions in the corpus.

ID	Emotion types	Emotion means	Emotion S.D.
1	trust	0.034167	0.001344
2	anticipation	0.02275	0.000722
3	fear	0.02	0.001155
4	sadness	0.016583	0.000862
5	joy	0.014333	0.001179
6	anger	0.01275	0.000595
7	surprise	0.01075	0.000595
8	disgust	0.007167	0.000373

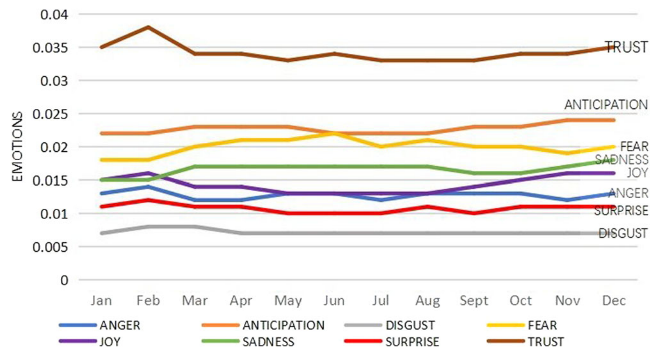

Fig. 3 Trajectories of the eight emotions in NYT unemployment-related news articles in 2020. The fluctuations of the emotions over the course of 2020 are illustrated, with the x-axis denoting the twelve months of the year and the y-axis indicating the emotional values.

To make a more in-depth analysis and discussion of the interaction between unemployment-related themes and the emotions within the constraints of the article's length, we focused on the two most prominent positive and negative emotions. Since a given word may convey different emotions in different linguistic contexts (Lei and Liu, 2021), to know what events and themes each emotion is associated with we examined the frequencies, colligations, collocates, and clusters of the most recurring words.

Positive emotions. "Trust" and "anticipation" rank the first and second among the eight emotions. Table 3 displays the overall frequencies of the terms linked to the two emotions in the whole corpus. These terms appeared at least 4 times in the high-frequency word lists across the 12 subcorpora.

The 11 most recurring words associated with "trust" can, to a great extent, explain the high value of this emotion. These words revolve around two issues: the government and economic policy, including "president, economy, united, congress, policy," and the essential elements in people's daily life, including "money, school, pay, food." This suggests that there was wide discussion in the newspaper in 2020 on economy-related policies, and people's income and living. Take "president" as an example, "sign" is the first verb that appears among its top collocates. An examination of the total 182 instances of the collocation indicates that, 87.4% (159/182) of the occurrences are about the signing of various economic policies and unemployment relief measures by the president. Another frequent lexical item is "congress". It is colligationally preceded or followed by the verbs "pass/passed (320), approved (114)", and the nouns "stimulus (181), relief (172), package (134), trillion (98), billion (144)" are among its top ten collocates. Two telling examples are as follows.

Table 3 The most recurring terms tagged with "trust" and "anticipation" in the corpus.

TRUST	president(11556) economy(8563) money(6906) united(6145) school(5378) pay(4823) food(4723) good(3804) congress(3638) policy(3299) found(3138)
ANTICI-PATION	time(12897) public(7561) money(6906) long(6016) pay(4823) good(3804) university(3572) plan(3449) top(3062)

Table 4 The most recurring terms tagged with "fear" and "sadness" in the corpus.

FEAR	pandemic(11672) government(8416) police(3361) risk(2850) change(2704) emergency(2580) case(2542) medical(2519) death(2260) force(2153) disease (1880) unemployed (1605)
SAD-NESS	pandemic(11672) lost(3368) risk(2850) late(2641) emergency(2580) case(2542) fall (2376) death(2260) recession(2109) leave(2084) unemployed(1605)

(1) The New York Times, April 3, 2020
Mr. Swagel said the unemployment rate could have reached 12 percent if not for the expected effects of the $2.2 trillion economic rescue package that *President Trump signed* last week.

(2) The New York Times, March 25, 2020
The Treasury has asked *Congress to approve* around $50 billion in emergency loans to shore up the airline industry.

In the above two excerpts, example (1) demonstrates the discussion in news articles about the possible effects of a policy that has been signed into law by the president, while example (2) illustrates the discussion about pushing the approval of a plan by the Congress. Such kinds of examples are numerous in the corpus.

For "anticipation", 9 terms occurred at least 4 times across the 12 subcorpora as high-frequency words tagged with the emotion, which, in addition to sharing some words with "trust" like "good, money, pay", are found to be terms associated with planning, the future, and expected effects of public policies, such as "time, long, plan" in Table 3. Take "long" as an example. An examination of its 2-word clusters shows that "long-term" (975), topping the list, is far higher than others in frequency, often followed with words like "effects/impact/consequences/unemployment/solution/ prospect". Another example is "plan". It is colligationally preceded or followed by the verbs "reopen/reopening"(165) and "unveiled"(31), while the nouns "trillion (96), stimulus (110), rescue (40), billion (101)", together with the two verbs, are among its top ten collocates. The following are two extracts about the uses of "long" and "plan".

(3) The New York Times, March 26, 2020
Many of the provisions are intended to offer lifelines to companies and workers over the coming months,….. But the *long-term consequences* of a $2 trillion bailout of the American economy are unknown.

(4) *The New York Times*, September 10, 2020
Senate Republicans on Tuesday released a pared-down coronavirus *stimulus plan*, which would provide federal aid to unemployed workers, schools, farmers, the Postal Service and small businesses.

Example (3) is from a report discussing the distribution of the money in the $2 trillion aid package passed at the beginning of the pandemic and the expected effects it might bring, while example (4) is about another stimulus plan targeted to more specific group of people and sectors. These examples, together with the colligations and collocates of "long" and "plan", suggest that "anticipation" is also related with the policy response to the pandemic and unemployment, with more attention to the possible effects of the policies.

Negative emotions. "Fear" and "sadness" top the four negative emotions. Table 4 presents the total frequencies of the terms annotated with the two emotions in the whole corpus. These terms appeared at least 4 times in the high-frequency word lists across the 12 subcorpora.

"Fear" ranks the first among the four negative emotions, which is in line with the results of emotion analysis studies on social media, especially at the early stage of the pandemic (Lwin et al, 2020). A closer observation of Fig. 3 reveals that its track along the timeline is different from those of other emotions, especially when compared with that of "sadness". While other emotions remain relatively stable from March to August, the value of "fear" reaches its peak in June, 2020. To explain this pattern we can again examine the most recurring terms annotated with the emotion. As shown in Table 4, there are 12 most recurring terms tagged with "fear", which appeared at least four times across the 12 subcorpora, the highest in number among the four emotions studied, which suggests that more events and themes are linked with the emotion. In general the terms can be classified into three groups based on their relations to each other.

The pandemic-related terms, including "pandemic, risk, change, emergency, case, medical, death, disease", take up the largest proportion in the list. This group of words not only excel in number, but also appear highly frequently in the corpus. Almost all of these words, in fact, are common and universal collocates of COVID-19 in the news about the pandemic (Nor and Zulcafli, 2020).

The second group of terms are related to the economy and unemployment, including "emergency, unemployed, force". "Emergency" is also included here because it frequently occurs in the context discussing unemployment, such as in "emergency unemployment insurance/benefits." "Force" frequently occurs in the 2-word clusters "labor force" (669) and "work force" (216) which together take up 41.1% of its occurrences.

It is noteworthy that "police" appears in the above list as the third group, which ranks the second after the term "pandemic" in the monthly high-frequency words associated with "fear" in June, 2020, and remains one of the most recurring words since then. Among its top ten collocates are "brutality (229), Minneapolis (131), protest (151), violence (131), custody (79), and Floyd (110)", which are all directed to the tragedy of George Floyd, a Black man who died on 25 May, 2020 after being handcuffed and pinned to the ground by Minneapolis police officers. This event was related to unemployment because, although job loss has been universal during the pandemic, it has been particularly devastating to people of color (Saenz and Sparks, 2020). Floyd's tragedy brought the sufferings of the black into lens, and thus sparked nationwide protests as well as intense coverage on news media. This is demonstrated by the following excerpt:

(5) The New York Times, May 28, 2020
African-Americans earn one-third as much as white residents. *They graduate from high school at much lower rates, are much likelier to be unemployed* and tend to live in households with significantly less wealth than their white counterparts.

As this example shows, the black people have suffered from ethnic inequalities in various aspects, which put them in a more vulnerable position during the pandemic.

"Sadness" ranks the second among the four negative emotions, which demonstrates an opposite pattern to that of "joy". As joy-sadness is the basic emotion pair of opposite experiences according to Plutchik's (1980) Wheel of Emotions, it is logical that a weak negative correlation is found between the two emotions ($r = -0.273$, $p = 0.390 > 0.05$). Before February, the value of "sadness" is lower than that of "joy"; it rises drastically after that, however, and is much higher than the latter. It remains at a high level from March to August and falls slowly; but from October to December, there is an evident rise again. An examination of its word list in Table 4 reveals that the two largest causes to "sadness" are still the deaths and diseases brought by the pandemic and individuals' financial problems and job safety.

It is noteworthy that the last two months in 2020 saw the evident rise of "fear" and "sadness" (Fig. 3), which, to a great extent, is attributed to the new surge of the pandemic in cold weather, as evidenced by the following extract:

(6) *The New York Times*, November 2, 2020
"*We are entering the most concerning and most deadly phase of this pandemic*," Dr. Deborah L. Birx, who helped lead the Trump administration's coronavirus response, delivered a stark private warning to White House officials.

The above analysis shows how the emotions conveyed in the unemployment-related news articles change over time in 2020 and what important events and themes are related to these emotions. "Trust" and "anticipation" are more closely associated with the discussions of policy response to the pandemic and the economy, and their expected effects. The fluctuation of negative emotions, however, is brought about by more varied factors, including the death and health risks of the pandemic, job safety, as well as nationwide protests against ethnic inequalities sparked by Floyd's death.

Discussion. There is no doubt that the public perception conveyed in unemployment-related news reportage is correlated with the evolution of unemployment; however, the corpus-based analysis of the news articles reveals that the emotional representation of unemployment on news media is also linked with some significant events and themes in 2020, which together outline the contours of this eventful year.

To begin with, the COVID-19 pandemic, with its immediate impact on the recession and mass job loss, is considered the basic driving force behind the change of unemployment-related public emotions. That the pandemic is the direct trigger of the recession and unemployment has been a fact widely evidenced by the public's experience which was shown in their social media (Nia et al., 2022b) as well as academic research in economy (Fairlie, 2020). The impact of the pandemic on public perception is particularly evident at the beginning and end of 2020. In February, 2020 the two sentiments begin to change, and in March the negative sentiments and emotions rise to the peak; the unemployment rate, however, started to rise substantially in March and did not reach the peak until April (Bureau of Labor Statistics, 2020). In the last two months of 2020, the negative emotions rise when there was a new surge in the pandemic, while unemployment rate remained the same (Bureau of Labor Statistics, 2020).

Moreover, the public perception is also associated with policy response to the pandemic and unemployment which have brought intense reportage and wide discussion on news media. The pandemic-driven unemployment, characterized with eruptive and large-scaled job loss in a short period of time, posed unprecedented challenges in its immediate need for action. From March, 2020, a number of monetary and fiscal policies have been implemented by Federal Reserve (Fed) and US government to provide stimulus to the economy and relief to those affected by the global disaster (Gape, 2023). On 6 March, 2020, for example, the CARES Act (Coronavirus Aid, Relief, and Economic Security Act), one of the three relief packages and the largest single relief package in the U.S. history, was signed into law (Gape, 2023), which was considered a well-timed piece of bipartisan legislation (Furman, 2020). The immediate, substantial policy response to a great extent helped curb the escalation of negative sentiments and emotions in March, which is congruent with the study of sentiments on social media (Park et al., 2022).

The policy response led to a relatively fast recovery. The CARES Act alone, for example, provided 30 percent of GDP in fiscal support in its initial months (Furman, 2020). The U.S. economy, which fell by about 32% in the second quarter of 2020, rebounded in the third quarter and ended the year with an increase of 4.0% (Bureau of Economic Analysis, 2021). Meanwhile, there was a continuous decline of unemployment rate which fell to 6.7% by the end of 2020 (Bureau of Labor Statistics, 2020). In spite of controversy on the long-term effect of the policies (Scanni, 2021), Barbieri Góes and Gallo (2021) argued that stimulus policies played a key role in preventing fluctuations in the labor market caused by the recurrent pandemic waves, reducing at the same time the negative effect of job losses on GDP. It is reasonable, therefore, to assume that this recovery and continuous decline of unemployment rate greatly contribute to the noticeable fall of negative sentiment and rise of positive sentiment from August, although other factors also play a part in the change, including the marked reductions in COVID-19 mortality as a result of higher social distancing (VoPham et al., 2020), and the increased availability of effective COVID-19 outpatient treatment (CDC, 2023b).

Furthermore, the public perception of unemployment conveyed on news media in 2020 is also correlated with nationwide protests induced by structural racism that is longstanding and deeply rooted within American society. The consequences of the COVID-19 pandemic have not been experienced evenly (Galea and Abdalla, 2020). The black communities suffered from more health risks and less medical care in the pandemic (Poteat et al., 2020). While millions of people across the US were laid off due to the mitigation measures, higher unemployment rates have been found among black and Hispanic workers compared with white workers (Fairlie et al., 2020). Blacks, together with Hispanic and other groups with a less privileged social status, also suffered from more mental repercussions brought by employment insecurity which was disproportionately concentrated among these groups (Lee et al., 2021). Against this backdrop, the killing of Folyd by the police naturally became the flashpoint for justifiable anger and civil unrest "not seen since 1968" (Galea and Abdalla, 2020: 228). The tragedy is considered to be related with the rise of "fear" in the study from June, 2020.

All in all, the evolution of the pandemic and unemployment, policy response, and the protests against racial inequalities, have worked together in shaping the public perception of unemployment in 2020 conveyed by the news media. The results of this study, characterized with the dominance of positive sentiments and emotions, are different from sentiment analysis studies of social media on COVID-19 and unemployment in which negative emotions, in general, are found more dominant (Lwin et al., 2020; Nia et al., 2022b). Despite the differences in the focused duration, topics and research methods, the fundamental reason for the disparities lies in the different scopes and functions between social media and news media. First of all, while social media are more focused on individual communication (Schrape, 2018), news articles, in general, are considered to convey more objective stories even though they tend to underreport risks and overstress benefits (Bubela and Caulfield, 2004). Secondly, topic coverage on social media is somewhat limited and more user-centered (Schrape, 2018), while news articles deal with various topics (Kim et al., 2016). This is best shown in the wide coverage of policy response in the news media, which has greatly contributed to the high value of "trust" and "anticipation".

Therefore, news media, as a watchdog, play a crucial role during the crisis. By disseminating public health and policy information, news coverage communicates risks to readers and shapes public perceptions through the amount, content, and tone of reporting (Mach et al., 2021). It also frames ongoing public debates about policy response, including conflicting priorities relevant to the timing or stringency of implemented policies (Laing, 2011). In 2020, the US led the world in disease rates due to disinformation and failures of national leadership in the pandemic (Evanega et al., 2020). While it is all agreed that the content and tone of the news have a bias toward conflict and negativity (Harcup and O'Neill, 2017), sufficient attention should be simultaneously paid to the policies and measures taken by the government at all levels to tackle the pandemic, economy, and unemployment. This constructive, solution-oriented reportage, still perceived as legitimate journalism, can evoke positive emotions, such as hope or elevation (Baden et al., 2019), which is particularly important for the public at the time of serious crisis.

On the other hand, however, we should be aware that the journalistic representation of the pandemic and unemployment is a mediated one. This mediated reality of the pandemic and economy is created through daily reporting and our dependence on the media for information in the year. While journalism has the power to influence society, it is itself also influenced and governed by a number of contextual constraints–the ideological, political, and economic circumstances with which it is surrounded (McChesney, 2008). In the relationship between journalism and politics, journalism is at risk of being the subordinate party. This is especially true in times of crisis or big political questions (Jacobsson, 2018). The unemployment, as one of the most important concerns in the pandemic, is part of the narrative of the crisis on news media that has been found to be highly politicized and polarized (Hart et al., 2020). While this study does not investigate the effects of such politicized and polarized news coverage on public opinion, their influence on public views in this presidential election year should not be neglected.

Conclusion

Incorporating sentiment, emotion, discourse, and timeline analyses together, this study explores the change of public perception of the pandemic-induced unemployment conveyed on news media in 2020. With sentiment analysis we find positive sentiment in the news articles is significantly higher than negative sentiment. Emotion analysis shows that "trust" and "anticipation" rank the first and second among the eight emotions, while "fear"and "sadness" top the four negative emotions. Complemented with discourse analysis, we find the emotional dynamics is linked with the evolution of the pandemic and unemployment, the policy response, and the protests against ethnic inequalities.

The study contributes to the understanding of media representation of public perception of unemployment during the pandemic in several important ways. First, while all the studies analyzed the sentiments on social media, this study focuses on public emotions presented on mainstream news media by professional journalists. Next, most studies, targeting at a much shorter duration during the pandemic, ignored the dynamic nature of emotions; our longitudinal analysis, however, traces the trajectory of sentiments and emotions in the whole 2020. Thirdly, corpus-based discourse analysis is employed as a complementary approach to emotion analysis to help identify the events and themes related with the public perception of unemployment on news media in 2020.

This study also bears important practical implications for the management of eruptive mass job loss as the pandemic-induced one in 2020. First of all, it is crucial that the government make an immediate response to stimulate the economy and provide substantial aid to the unemployed when a large number of employees are laid off. Furthermore, it also suggests that traditional news media like newspapers play a central role in timely information dissemination with regard to economic policies and relief measures at this critical time. The solution-focused constructive reportage is important to boost people's hope and confidence at the time of severe crisis.

Finally, our study also has some limitations. Above all, our calculation of sentiment and emotion values are based on word counts for words annotated in the NRC lexicon. Although the lexicon-based approach to sentiment analysis is complemented with discourse analysis, it is impossible to make a thorough analysis of the concordance lines of all words annotated with sentiments and emotions. Since a word can have multiple meanings and senses which are highly dependent on the context and domain (Khoo and Johnkhan, 2018), the neglect of context may affect the accuracy of the calculation. Secondly, only one newspaper is selected for data collection, which to some extent, influences the representativeness of the data. Later research, therefore, could improve accuracy by including more newspapers and combining lexicon-based and machine learning approaches together.

Data availability

The datasets generated and analyzed during the current study are available at https://doi.org/10.6084/m9.figshare.25879897.v1. This link provides information on the NRC lexicon categories for sentiments and emotions of the corpus, their monthly calculated values, and the top 10 high-frequency words associated with the emotions for each month.

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Author contributions

Both authors conceived the analysis, designed the methods, and drafted the manuscript. The first author collected data and performed data analysis, and the second author conducted the revision and editing.

Competing interests

The authors declare no competing interests.

Ethical approval

This article does not contain any studies with human participants performed by any of the authors.

Informed consent

This study did not involve human participants and no informed consent was required.

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